The Costs of Adapting to Climate Change for Infrastructure

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DEVELOPMENT AND CLIMATE CHANGE

The Costs of Adapting to Climate Change for **Infrastructure**

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Note: This paper is based upon work that has been commissioned by the World Bank as part of the Economics of Adaptation to Climate Change study. The results reported in the paper are preliminary and subject to revision. The analysis, results, and views expressed in the paper are those of the authors alone and do not represent the position of the World Bank or any of its member countries.

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ABSTRACT

An approach to estimating the costs of adapting to climate change is presented along with results for major components of infrastructure. The analysis separates the price/cost and quantity effects of climate change. The first component measures how climate change alters the cost of a baseline program of infrastructure development via changes in design standards and operating costs. The second component measures the effect of climate changes on the long-run demand for infrastructure. The results indicate that the price/cost element is usually less than 1 percent of baseline costs, while the quantity effect may be negative for many countries.

1. SETTING THE SCENE

This paper presents the results of a global analysis of the costs of adapting infrastructure to climate change over the period from 2010 to 2050. The analysis was carried out as part of the World Bank's Economics of Adaptation to Climate Change study. In this context, infrastructure has been given a rather broad definition. It includes the usual types of infrastructure services, including transport (especially roads, rail, and ports), electricity, water and sanitation, and communications.[1] In addition, urban and social infrastructure such as urban drainage, urban housing, health and educational facilities (both rural and urban), and general public buildings have been included.

The basic approach is extremely simple. For any country j and date t (t = 2010, 2015, …, 2050), we start from the assumption that there is some "efficient" level of provision of infrastructure of type i, which will be denoted by Q_{ijt}. The efficient level of infrastructure is that which would be reached if the country had invested up to the point at which the marginal benefits of additional infrastructure just cover the marginal costs—both capital and maintenance—of increasing the stock of infrastructure. It is often argued that developing countries tend to underinvest in infrastructure and that the extent of underinvestment is particularly large for the poorest countries (AICD 2009). This is an important development issue, which is not directly related to climate change. Hence, the approach attempts to strip out the effects of country differences in their actual provision of infrastructure by establishing a common benchmark that depends upon factors such as population and income.

In the period from t to t+1, for example from 2010 to 2015, the country will have to invest in order to meet the efficient level of infrastructure in t+1 and to replace infrastructure in situ at date t, which reaches the end of its useful life during the period. Thus, the total value of investment in infrastructure of type i in country j and period t is

$$I_{ijt} = C_{ijt}[Q_{ijt+1} - Q_{ijt} + R_{ijt}] \tag{1}$$

where C_{ijt} is the unit cost of investment and R_{ijt} is the quantity of existing infrastructure of type i that has to be replaced during the period. The change in the total cost of infrastructure investment may be expressed in terms of the total differential of (1) with respect to the relevant climate variables that affect either unit costs or efficient levels of provision for infrastructure of type i:

$$\Delta I_{ijt} = \Delta C_{ijt}[Q_{ijt+1} - Q_{ijt} + R_{ijt}] + (C_{ijt} + \Delta C_{ijt})[\Delta Q_{ijt+1} - \Delta Q_{ijt} + \Delta R_{ijt}] \tag{2}$$

An equivalent equation may be derived for the costs of operating and maintaining infrastructure. In the discussion that follows, the first part of the right-hand side of equation (2) is referred to as the Delta-P component of the cost of adaptation, while the second part is referred to as the Delta-Q component. These components themselves cover a number of ways in which climate change may cause changes in the costs or quantities of providing infrastructure services.

Delta-P. At the simplest level, changes in temperature, precipitation, or other climate variables may alter the

1 Limitations on the availability of comparable data meant that it was not possible to cover gas networks in the study. However, the costs of adaptation are likely to be minimal apart from any impacts on the level of demand, which are likely to be similar to the pattern for electricity.

direct cost of constructing infrastructure to a standard specification. For example, seasonal weather variations can increase the costs of building. However, this is a minor factor. More important is the impact of climate change on the design standards that are applied in order to maintain the quality of infrastructure services provided by a unit of infrastructure, such as a kilometer of paved road or a fixed telephone connection (See Canadian Standards Association 2006 for a discussion of this issue).

a. Changes in the frequency and/or the severity of storms, flooding, and other extreme weather events may compromise the performance of infrastructure designed to existing standards. Hence, it is common to refer to "climate proofing" investments or ensuring "climate resilience." The study starts from the basis that design standards should be adjusted so as to deliver the same level of performance as would have applied if climate change had not occurred. Thus, if roads or buildings are currently constructed to withstand a 1-in-50 or 1-in-100-year flood or wind storm, then the same design standard should apply, but under the circumstances of a changed frequency or severity of those events. The changes in the unit costs—ΔC_{ijt} —represent the costs of building infrastructure that delivers the same level of performance in the face of different climatic stresses. The derivation of the cost changes, expressed as dose-response relationships for different climate stressors, are described in Appendix 1. The dose-response functions are applied to estimates of the average values of climate variables under a scenario of a stable climate and alternative scenarios for climate change by country.[2] This gives a series of cost increases—at constant 2005 prices—by type of infrastructure, country, and time period. When applied to the baseline projection of infrastructure demand, we obtain the Delta-Q cost of adaptation; that is, the difference between the cost of the baseline investment program for a stable climate and for a changing climate. A similar exercise may be carried out for operating, maintenance, and replacement costs in order to calculate the increment in annualized infrastructure costs as a consequence of climate change.

b. Delta-Q. The quantities of infrastructure assets required (holding income constant) will change as a consequence of different climatic conditions. Again, this has two dimensions. The first is that climate change may change the level or composition of demand for energy, transport, and water at given levels of income, so we need to calculate the net impact of these changes in terms of capital and operating costs. The second is that climate change will mean that countries have to invest in specific additional assets in order to maintain specific standards of protection for non-infrastructure activities.

The Delta-P dimension of the study is uncontroversial in principle, though more or less difficult in practice. Various organizations have made broad brush estimates of the cost of "climate proofing" existing investment programs in developing countries (UNFCCC 2007; McGray et al. 2008). Typically, the analysis starts from a baseline program in investment by time of infrastructure. Then, an estimate is made of the percentage increase in unit costs required to ensure that investments are resilient to climate change.

One problem with the "climate proofing" approach concerns the investment program to which the cost of climate proofing should be applied. For some sectors or countries/regions, it is possible to start from a detailed inventory of infrastructure assets and then to ask what investments will be required to meet future demand for infrastructure services. The best example of this approach is a study of the costs of adaptation to climate change in Alaska (Larsen et al. 2008). However, this type of exercise requires an inventory of infrastructure assets and it does not take account of future investment in infrastructure.

In the case of developing countries, many institutions that are concerned with adaptation to climate change for infrastructure draw a distinction between (a) the cost of eliminating the "development deficit,"—that is,

2 Most climate models generate projections for 2° grid squares. For this study, these projections have been downscaled to 0.5° grid squares and then population-weighted averages of the grid square values have been computed for each country. Thus, references to climate variables by country in this paper should be construed as referring to the population-weighted averages of, say, precipitation for the various grid squares that cover the country.

the gap between the infrastructure that a country "ought" to have and the infrastructure that it actually has—and (b) the cost of adapting to climate change on the assumption that the country has an efficient level of infrastructure. The former is seen as a development problem, while the latter is a climate change problem. Even though it is understood that money is fungible, the two elements of total investment in infrastructure might be financed out of different pots of money.

The corollary of this distinction between adaptation and the development budget is that the baseline program for infrastructure investment used in constructing the Delta-Q should not be derived from actual or planned investment in infrastructure. Instead, it should reflect the "efficient" demand for infrastructure.[3] This is no simple task. The World Bank has recently completed a detailed assessment of infrastructure investment needs in 22 African countries, assuming a catch-up from actual to efficient provision over a decade to 2020 (AICD 2009). That exercise involved very substantial work and cannot be extended to all countries in a short period. Instead, the analysis has to be based on an econometric model that can be used to construct projections of the efficient demand for infrastructure up to 2050.

While the principle of drawing a distinction between the "development deficit" and adaptation to climate change is widely followed in international negotiations, many economists consider that the distinction is either unworkable in practice or simply wrong as a matter of economic logic. The reason is that most assessments of the "efficient" demand for infrastructure ignore the question of resources. A specific country might wish to have more roads, schools, or hospitals than the stocks that are currently in situ, and the rest of the world might agree that this would be a desirable goal. But, this is nothing more than a wish list independent of the resources that are available. With limited resources some countries may choose to spend their funds on providing better roads or more healthcare services.

3 This paper will refer to the (efficient) demand for infrastructure and will not attempt to address the question of how far the actual stocks of infrastructure are constrained by the supply of infrastructure assets. In effect, we assume that (a) we can identify an equation describing the long-run demand for infrastructure, and (b) supply constraints are not relevant when projecting the future investment program in calculating adaptation costs.

Relying either upon wish lists or on the envelope of what other countries at similar incomes have invested ignores the trade-offs that all governments have to make. Even if external assistance is available to fund capital projects, it is common experience that lack of funds for operations and maintenance may lead to rapid deterioration in the services provided by stocks of infrastructure assets.

Thus, it may be argued that the analysis should not be based on some notional "efficient" level of infrastructure, but should start from the actual levels and growth of infrastructure based on decisions that reflect real constraints on budgets and the associated priorities. To examine whether the distinction is important in practice, the full study has used two sets of baseline projections of demand for infrastructure. The "frontier" projection is derived by using frontier methods of estimation to estimate econometric equations that characterize the envelope of infrastructure demand given exogenous variables such as income, population, urbanization, etc. This is intended to provide an estimate of the "efficient" level of infrastructure demand as envisaged in discussions of the development gap. In contrast, the "panel" projection uses conventional projections derived from econometric estimates of the average relationship between infrastructure and the exogenous variables.

The difference between the Delta-P estimates using the two sets of baseline projections is not as large as some might expect. There is an important reason for this. We find that the relative gap between the frontier and panel projections tends to narrow, because there appears to be convergence toward standard patterns of infrastructure provision. Further, the income elasticity of demand for infrastructure is generally less than 1 for the frontier demand equations and is lower than the equivalent income elasticities for the average demand equations. For the frontier baselines projection, these factors lead to a lower level of new investment in infrastructure, but a higher level of expenditure on replacing and maintaining the initial level of infrastructure. Under the panel baseline projection, lower levels of spending on replacement and maintenance are offset by higher spending on new investment. Depending on the initial development gap and the timing of new investment, it is possible—though not usual—for the cost of adaptation to be larger for the average baseline than for the frontier baseline.

In this paper we will focus exclusively upon the panel projections derived from panel data models rather than the frontier models. This is consistent with the view that the distinction between the development deficit and the adaptation deficit is difficult to draw under the best of circumstances and may not be useful in practical terms.

The second, Delta-Q, aspect of this work concerns the impact of changes in climate on the demand for infrastructure. To approach this issue, we have to consider the mechanisms by which changes in climate may affect the demand for infrastructure and how we might identify these consequences. For example, it is generally accepted that demand for electricity depends upon climate in general, but it is not so easy to identify the key climate parameters when estimating the demand for electricity or for electricity-generating capacity. Note that even these two variables may be subject to different influences because the seasonal or diurnal pattern of electricity demand is strongly influenced by climate.[4] Part of the difficulty is that the outcome depends upon the relative weights assigned to different factors. An increase in average temperatures will lead to less demand for heating in the colder seasons but more demand for cooling in the warmer seasons. The overall direction of change is not easy to predict and is likely to depend upon the way in which we set up the problem.

Electricity is simple to think about by comparison with roads or other transport infrastructure because there is an intuitive sense of the mechanisms involved in a relationship between climate variables and the stock of electricity-generating capacity. But it would be wrong simply to impose the assumption that climate has no effect on the demand for roads. Patently, climate variables do affect the structure of economic activity holding other factors constant —for example, through the level and composition of agricultural output—and this will influence the nature of investment in roads. There are more complex but potentially larger effects operating through the economic geography of urban life, industry, and commerce; that is, in the ways in which we organize economic activity in space. Small changes may have significant consequences for the level of investment in infrastructure.

While the principle that climate change may affect the demand for infrastructure seems straightforward, the task of estimating the Delta-Q costs of adaptation is much more difficult for two general reasons.

a. Many of the impacts of climate on demand for infrastructure are long term in nature. This may not be true for electricity, but any influence of climate on the demand for roads will operate via the path of economic development over a period of one, two, or many decades. There are two consequences. First, we should not think of the Delta-Q component of the costs of adaptation as arising on a regular schedule every five years. The calculation merely identifies additions to and subtractions from a liability (or asset) that will materialize in future as economic activity adjusts to the changes in climate that are taking place. Second, in planning for future infrastructure development, governments need to consider how climate change may affect the amount and type of infrastructure that is required if it will influence future patterns of economic activity.

b. In practice, there is no way of examining the empirical impact of climate on the demand for infrastructure other than through some form of panel data analysis—pooling data for countries, regions, states, or other geographical units over time. Inevitably, climate is a cross-sectional variable (since year-to-year variations are weather), which may easily be confounded with other cross-section fixed effects. This has prompted various criticisms of the Ricardian approach to identifying the impact of climate change on agriculture or GDP on the grounds that climate variables are acting as a proxy for non-climate factors such as institutions. Some economists draw the conclusion that climate variables should not be used in this way. We do not accept this view, since it

4 There are also limitations on what one can obtain from climate projections. For example, it is conventional to include degree-days as a climate variable in equations predicting energy demand because of heating requirements. The number of heating degree-days for a particular location is calculated from the truncated distribution of temperatures below some threshold—often 18°C—either on an hourly or a daily basis.

> closes off any possibility of estimating the impact of climate change on overall demand for infrastructure. Instead, we have carried an extensive econometric analysis of the role of climate variables in modeling the demand for infrastructure. The details are technical and take up a large amount of space, so that they are reported in a separate paper (Hughes 2010). The issues and results are summarized in sections 4 and 5 below. Our results suggest that the demand for some categories of infrastructure is affected by different climate variables with important interactions with income per capita and urbanization.

The results of our econometric analysis suggest that the absolute magnitude of the Delta-Q component of adaptation should not be ignored in the long run. On the other hand, the Delta-P component is much more predictable as a basis for discussing plans for adapting to climate change. For these reasons, our detailed estimates of the costs of adaptation by 5-year period up to 2050 concentrate on the Delta-P component, while the Delta-Q estimates are presented as indicative estimates for the whole period.

2. DATA

The core data used in this study is the World Development Indicators (WDI) database published in 2008 by the World Bank, which provides panel data for up to 168 countries and the years 1960 to 2006. The year 2005 is treated as the base year for all of our estimation. Our work relies on the 2008 version of the database. One crucial consequence is that the purchasing power parity estimates of GDP per person rely on a version of the 2005 ICP baseline due to appear as Penn World Tables (PWT) Version 7. These estimates cover the period 1980–2007 for a large set of countries. They have been extended backwards to 1960 by splicing estimates from PWT Version 6.2, which uses the 2000 ICP baseline. Country gaps have been filled by the standard approach of using a quadratic equation linking GDP per person in constant (2000) USD at market exchange rates to GDP per person at constant (2005) PPP exchange rates.

The WDI data has been supplemented with data on infrastructure availability from a wide variety of sources, including other international organizations (FAO, ITU, WHO, UNICEF, UPU), official country data (especially census data), and various systematic surveys such as Demographic and Health Surveys (DHS) and Living Standards Measurement Surveys (LSMS), which are broadly consistent across countries. Even so, the final dataset is very patchy in terms of coverage, especially for earlier periods. The panels are unbalanced and there are many missing values for intermediate years. Thus, it is not possible to make use of econometric specifications involving autoregressive or similar errors over time.

A further remark concerns the nature of the data relating to different types of infrastructure. In a few cases, we have direct measures of the quantity of infrastructure assets—for example, kilometers of paved or all roads, kilometers of rail track, MW of generating capacity. More commonly we have to rely upon measures of infrastructure output—for example, numbers of households connected to electricity, water, or sewer systems. In practice, the efficient levels of infrastructure assets are closely linked to these output or input variables, so we believe that it is reasonable to base our projections on an analysis of these infrastructure indicators.

3. CLIMATE CHANGE

Describing the historic climate in a manner that is compatible with macroeconomic data is far from straightforward without any of the complications of projecting climate change into the second half of the 21st century. The literature on the influence of climate on economic variables has tended to rely upon average values of climate variables, primarily temperature, measured for the capital city of the country. The classic dataset is the data compiled by NCAR—NOAA's National Center for Atmospheric Research in Boulder, Colorado—for weather stations around the world identified by their World Meteorological Organization reference code. The difficulty with this dataset is that there is no consistency across stations in the data that is reported. We have examined average data for capital cities derived from weather stations in or near the capital—including, for example, nearby airports. This is used to obtain an average elevation for the capital city, but there are too many missing values to rely upon the climate variables for our econometric analysis.

The Climate Research Unit at the University of East Anglia has compiled a series of historic weather data for 0.5 degree grid squares for land areas of the globe. Summary statistics have been computed for each grid cell for monthly average, maximum and minimum temperatures (in degrees C), and precipitation (in mm) for the period 1901–2002. The distribution of temperatures is generally accepted as being well-approximated by the normal distribution, so it was sufficient to compute the mean and standard deviation for each grid cell. For precipitation, the distribution is closer to the log-normal, so the mean and standard deviation of ln(precipitation+1mm) were calculated in addition to the mean of precipitation.[5]

Country estimates of the climate variables were constructed using grid cell means for monthly mean, maximum, and minimum temperatures and precipitation. The primary variables are population-weighted averages using the population in each country in each grid cell to weight the grid-cell means, thus reflecting the average exposure for the population of each country.[6] Alternative sets of country means weighted by (a) the land areas in each cell, and (b) the inverse of population in each cell were also constructed. The reason for doing this is linked to the demand for transport and other types of hard infrastructure. Consider a country such as Australia. The population is concentrated in the coastal areas of the continent, while the interior—with very different climatic conditions—is very thinly populated. So the population-weighted averages will reflect the climate on the coast whereas the inverse population-weighted averages reflect the climate in the interior, while the area-weighted averages fall in between.[7] The correlations between the population-weighted and inverse population-weighted climate variables are shown in Table 1 along with correlations with historic demographic variables used as instruments for institutional development as discussed in Section 4.

The primary climate variables used in the econometric analyses are the two weighted means for (a) annual average temperature (computed as the average of monthly average temperatures) in ˚C; (b) total annual precipitation (computed as the sum of monthly average precipitation); (c) the temperature range (the average maximum temperature in the hottest month, the average minimum temperature in the coldest month); and (d) the precipitation range (average precipitation in the wettest month, average precipitation in the driest month).

One point to note is that annual average temperature measured in degrees C is negative or very small in a number of countries, especially for the inverse population-weighted means. Because of the use of the logarithmic transform, it is necessary either to exclude countries with extreme temperatures or to apply some linear shift to temperatures. The transformation adopted was to add 40˚C to all temperatures. This value reflects the range from the minimum value of the monthly minimum temperature (-29.1˚C) and the maximum value of the monthly maximum temperature (+46.9˚C). Of course, the shift has no effect on the temperature range.

The choice and use of climate projections to 2050 and beyond is considerably more complex. Global climate models (GCMs) are programmed to produce projections of different variables for different time periods. At a micro scale, there are large differences between the results generated by the various models, so that it is necessary to be very careful about relying upon a single model. The standard deviation of projections for any one grid cell is typically large relative to the mean value of the projected change up to 2050 or even 2100. Further, the problem is more serious than simple models may suggest. Our econometric models suggest

5 The shift of +1mm is required because precipitation is zero for many months at some grid squares, which would generate missing values without the shift.

6 There is one complication. Just over 10 percent of grid cells cover more than one country, but the data only provide the land area of each country in each grid cell plus total population in the grid cell. It is, therefore, necessary to assume that population density is uniform over these grid cells so that population is split between countries in the same proportion as land area.

7 We have tested whether using either the inverse-population-weighted and area-weighted means instead of or in addition to the population-weighted means improves the performance of our equations. In all of the cases that we have examined, the area-weighted climate variables are dominated by the inverse population-weighted (ipop) climate variables.

TABLE 1. CORRELATION MATRIX OF CLIMATE VARIABLES AND HISTORIC DEMOGRAPHIC INDICATORS

	Population-weighted climate				Inverse population-weighted climate				
	Average temper-ature	*Precipi-tation*	*Temper-ature range*	*Precipi-tation range*	*Average temper-ature*	*Precipi-tation*	*Temper-ature range*	*Precipi-tation range*	*Birth rate 1950–54*
Population-weighted climate									
Average temperature	1.000								
Precipitation	0.229	1.000							
Temperature range	-0.656	-0.650	1.000						
Precipitation range	0.600	0.774	-0.618	1.000					
Inverse population-weighted climate									
Average temperature	0.830	0.151	-0.630	0.433	1.000				
Precipitation	0.083	0.811	-0.576	0.525	0.070				
Temperature range	-0.563	-0.612	0.943	-0.526	-0.598	-0.646	1.000		
Precipitation range	0.373	0.789	-0.630	0.775	0.283	0.885	-0.631	1.000	
Historic demographic indicators									
Birth rate 1950-54	0.728	0.042	-0.373	0.510	0.637	-0.106	-0.293	0.215	1.000
Infant mortality 1950-54	0.595	-0.027	-0.201	0.430	0.528	-0.118	-0.165	0.183	0.821

Source: Authors' estimates using data for 157 countries with non-missing data for GDP, population, urbanization, and generating capacity in 2005.

that the ranges between maximum and minimum monthly temperatures and precipitation are often the primary drivers of infrastructure demand. This means that the projections used to calculate the Delta-Q costs must be based upon climate scenarios that generate monthly maximum and minimum temperatures as well as average temperatures, which restricts the set of GCMs that can be used. But even more important, the variance of the difference between two variables is the sum of their variances minus their covariance. Under most plausible outcomes, this will exceed the variance of each element, so that the uncertainty about climate ranges will be higher than for climate means.[8]

For the main scenario analysis in this study, we have used results from the NCAR CCSM-3 and CSIRO-3 models (abbreviated to NCAR and CSIRO). These have relatively similar changes in the global moisture index, but they differ significantly in their patterns of climate change at the regional and country level. The models are part of a larger set of 26 GCMs that have been examined in detail by the MIT Joint Program on the Science and Policy of Global Change. As part of their analysis, the MIT group has down-scaled the climate projections to match the 0.5 degree grid cells used for the historic climate data, so population- and area-weighted means were constructed for the countries covered by our study for the NCAR and CSIRO scenarios.

These projections are not sufficient for the Delta-P analysis, because design standards for certain types of infrastructure are driven by extreme values rather than monthly average values. However, GCMs are not capable of generating reliable estimates of daily maximum/

8 This is particularly the case for the precipitation range. Generally, climate change projections suggest that monthly maximum and minimum temperatures will move roughly in line with average temperatures. That is certainly not the case for precipitation since in many places it is expected that rainfall patterns will become more uneven with zero or even negative covariance between changes for the driest and wettest months.

minimum temperatures, precipitation, or wind speed, so it is necessary to deal with this requirement in an indirect manner. We have proceeded as follows:

a. Use the normal or log-normal distributions of monthly averages of maximum/minimum temperature and monthly precipitation to estimate the 99th percentile of monthly maximum temperature, the 1st percentile of monthly minimum temperature, and the 99th percentile of maximum monthly precipitation.

b. Express these percentiles as a ratio of the maximum/minimum of monthly average maximum/minimum temperatures and the maximum monthly precipitation and assume that these ratios will remain broadly constant in the future.

c. Apply the ratios of the 99th/1st percentiles to the associated monthly extremes for 2050 in order to compute the change from extreme values for the historic climate to extreme values for the climate scenario in absolute units—degrees C or mm of rainfall.

d. In the case of wind speed, we have estimated the elasticity of the 99th percentile of wind speed with respect to the 99th percentile of precipitation by fitting extreme value distributions to the historic climate data and used the change in maximum precipitation to project changes in extreme wind events.

4. ECONOMETRIC SPECIFICATIONS

In considering the specification of the econometric analysis, it has to be remembered that the goal is to generate projections of the average demand for infrastructure up to 2050, whether or not these are affected by climate. We are not trying to examine the factors that drive the actual amounts of infrastructure assets supplied today or in the past. The key implication is that it is not appropriate to include, for example, indicators of governance or institutional development in the analysis. These may be relevant factors explaining actual outcomes for individual countries today. But they are not relevant when we wish to make projections 40 or more years into the future, since it is neither possible nor desirable to attempt to project how governance or institutions will evolve over that period.

To the extent that (a) institutional factors influence the current level of infrastructure provision, and (b) there is a correlation between institutional development and GDP per person or urbanization, then the impact of institutional development will be (partly) captured by the coefficients on GDP per person or urbanization in the reduced form discussed below. This is one reason why the elasticities of infrastructure demand with respect to these variables may be higher when estimated using a sample of all countries than for a sample of high-income countries only. But, equally, there are many other factors that may affect the reduced form elasticities.

Quite apart from matters of econometric philosophy, the nature of the data available for the purpose of making projections of future demand for infrastructure has an important influence upon the specification of the models. There are a very limited number of variables for which independent projections extending to 2050 have been constructed and can be used. In addition to the climate variables discussed above, these are total population, the age structure of the population, urbanization, and growth in income (GDP per capita measured at purchasing power parity), plus a number of geographical features, which act as country-fixed effects.[9]

The basic approach for the econometric analysis is to develop a reduced form specification of the efficient demand for the services provided by each type of infrastructure—for example, paved roads or railways.[10]

9 The demographic projections are based on the medium fertility projection in the UN Population Division's 2006 revision, which is linked to the urbanization projections. The central scenario for growth rates for GDP per person at purchasing power is computed by taking the average of five economic integrated assessment models— Hope (2003), Nordhaus (2002), Tol (2007), IEA (2008) and EIA (2008). The average growth rate for world GDP in real terms is very close to the IPCC A1 SRES scenario, but the country growth rates are not based upon the downscaled versions of that scenario since those were constructed with a base data of 1990 and the relative country weights are very out of date. The sources of the population and income projections are described in a separate note.

10 There is an extensive literature, much of it originating in the World Bank, on developing econometric models to identify links between

We assume that the structural equation defining the efficient demand for infrastructure type i in country j in period t may be written as:

$$Q_{ijt} = f_i\{P_{jt}, Y_{jt}, C_{ijt}, X_{jt}, Z_{ijt}, V_{jt}, t\} \tag{3}$$

The variables are defined as follows:

- P_{jt} is the population of country j in period t;[11]
- Y_{jt} is average income per head for country j in period t;
- C_{ijt} is the unit cost of infrastructure type i for country j in period t;
- X_{jt} is a vector of country characteristics for country j in period t;
- Z_{ijt} is a vector of economic or other variables that affect the demand for infrastructure type i for country j in period t; and
- V_{jt} is a vector of climate variables for country j in period t.

We can observe or project values for some of these variables, notably P, Y, X, and V (dropping subscripts). For the other variables we assume that:

$$C_{ijt} = c_i\{Y_{jt}, X_j, Z_{ijt}, V_{jt}, t\} \tag{4}$$

and

$$Z_{ijt} = g_i\{Y_{jt}, X_{jt}, V_{jt}, t\}. \tag{5}$$

Solving for Z_{ijt} and C_{ijt} allows us to write the reduced form as

$$Q_{ijt} = h_i\{P_{jt}, Y_{jt}, X_{jt}, V_{jt}, t\} \tag{6}$$

Since there are no strong priors on the appropriate functional forms for $f_i\{\ \}$, $c_i\{\ \}$, and $g_i\{\ \}$, we can use a standard flexible functional form to represent the demand equation $h_i\{\ \}$ in terms of the explanatory variables. We have adopted a restricted version of the translog specification for all variables other than population. Using the notation $x_j=\ln(X_j)$, the general translog function for infrastructure services may be written as:

$$\begin{aligned} d_{ijt} = \alpha_i + \beta_{pi} p_{jt} + \beta_{yi} y_{jt} + \sum \beta_{xim} x_{mjt} + \\ \sum \beta_{vir} v_{rjt} + \gamma_{yi} y_{jt}^2 + \sum \gamma_{xim} x_{mjt}^2 + \\ \sum \rho_{im} y_{jt} x_{mjt} + \sum \varphi_{ir} y_{jt} v_{rjt} + \\ \sum \sigma_{imn} x_{mjt} x_{njt} + \sum \phi_{imr} x_{mjt} v_{rjt} \end{aligned} \tag{7}$$

In practice, it is often difficult to estimate the full translog specification using the more complex econometric models, so the approach adopted was to start with the log-linear specification and then test whether the coefficients on the quadratic and cross-product terms are significant. Because this involves repeated testing of overlapping specifications, we have followed the spirit of the Bonferroni adjustment to test statistics by requiring that any coefficients retained in the model are significantly different from zero at the 1 percent level using conventional statistical tests.[12]

We have noted that including climate variables in equations for the demand for infrastructure may be challenged by some economists, especially if one goes on to assume that future demand for infrastructure will be affected by projected changes in these climate variables. The reason for the debate is that climate variables are believed to act as a proxy for institutional and other factors that determine actual outcomes, partly as a consequence of historical patterns of development (Acemoglu et al. 2001; Albouy 2008; Dell et al. 2008; Horowitz 2008. For example, attempts have been made to estimate a relationship linking income per person

infrastructure investment and economic growth and to project future investment requirements for infrastructure in developing countries—see Fay and Yepes (2003), Estache et al. (2005), and AICD (2009).

11 For some types of infrastructure, total population may be replaced by population in each age group; i.e., the number of children (ages 0 to 14), the number of elderly (ages 65+). The country-fixed effects include country size and the proportions of land area that are desert, arid, semiarid, steep, or very steep using standard FAO land classifications. In addition, we have used the proportion of land that has no significant soil constraints for agriculture.

12 In fact almost all of the coefficients are significantly different from zero at the 0.1 percent level. The exceptions to this procedure relate to linear terms in exogenous variables when one or more of the quadratic terms is significant at the 0.1 percent level. In such cases the linear term is retained, since it may be important for scaling the predictions.

and average temperature as a basis for measuring the impact of climate change at highly aggregated level. Indeed, any simple correlation of these variables appears to show that a higher average temperature (usually for the capital city of the country) is associated with lower average income per person. But even this relationship is complicated by the role of natural resource endowments. Acemoglu et al. (2001) suggest that, in part, temperature is serving as an instrument for institutional development, so they include historical mortality rates in their analysis on the grounds that this is an alternative—and better—proxy for institutional development.

The strategy adopted for our analysis relies on a number of alternative ways of dealing with this problem.

a. The Acemoglu et al (AJR) study used colonial (mostly 18th century) mortality as an instrument for institutional development and found that this had a very significant coefficient in their equations for recent economic growth. However, estimates of colonial mortality are not available for more than one-half of the countries in our sample and, in any case, there is considerable controversy about the reliability of the estimates that have been used. Instead, we have used an alternative set of instrumental variables. The UN's population statistics include a variety of demographic variables for the early 1950s for almost all countries. These provide good instruments because they are closely correlated with the historical endowment of both institutions and infrastructure, but demographic changes over the past 50 years mean they are less associated with current patterns.[13] Two instruments have been used—the crude birth rate and infant mortality. These two were chosen because they capture the highest proportion of the cross-country variation of the demographic variables examined. Reflecting their special role, these variables were included on their own without quadratic terms or cross-products with other explanatory variables. Consistently, one or both of the variables have coefficients that are significantly different from zero at the 95 percent or 99 percent levels. For this reason, the variables are included in all of the models discussed below. So, it must be remembered that—even without further controls for the possible role of climate as an instrument for institutional development—the analysis starts from a point that matches the state of the art in the current literature.

b. The role of climate as an instrument for institutional development is a geographical argument—that is, it is about the geography of regional development—as much as it is about climate per se. Thus, the natural approach— again made difficult in the past by data limitations—is to consider the use of spatial econometrics in which spatially weighted values of variables are used as instruments for institutional and other factors. The standard model of spatial interaction (or autocorrelation) is:

$$y_i = \alpha + \varphi \sum_{j \neq i} W_{ij} y_j + \beta x_i + \varepsilon_i \qquad (8)$$

where the matrix W is a matrix of weights capturing the spatial influence of location j on location i, φ is called the spatial autocorrelation coefficient, and ε is the error term whose distribution depends upon the model specification. The inverse-distance model has been used for this analysis for which the elements of W are proportional to the reciprocal of the distance between the population centroids for countries i and j up to a maximum of 2,500 km.[14] The W matrix is normalized so that the row sums are equal to 1. The equations are estimated using panel GMM with spatially weighted values of population, GDP per person, urbanization, and country size as instruments. The details of the analysis are given in a separate paper, but the overall

13 The actual variable used in the AJR study is ln (settler mortality). For 63 countries in their samples (excluding Bahamas), the correlations between ln (settler mortality) and our historic demographic variables are 0.46 for ln (crude birth rate), 0.67 for ln (infant mortality), and -0.69 for ln (life expectancy). The correlations with AJR's proximate indicator of institutions (average protection against expropriation risk 1985–95) are -0.58 for ln (settler mortality), -0.57 for ln (crude birth rate), -0.69 for ln (infant mortality), and 0.65 for ln (life expectancy). Hence, our historic demographic indicators should provide better instruments for institutional influences than AJR's use of settler mortality.

14 The distance band is chosen to ensure that all countries have at least three "neighbors" within the band. This is a particular concern for large/isolated countries or territories such as Australia, Brazil, Canada, and Papua New Guinea. Reducing the distance band to 2,000 km would mean that seven countries or territories have only one "neighbor" within the band, while reducing it to 1,500 km excludes Australia, Mongolia, Papua New Guinea, and Timor-Leste as having no "neighbors."

conclusion is that (a) the spatial interactions are consistently insignificant, and (b) including them does not alter the role of the climate variables in our equations.

c. Setting aside the spatial argument, the central econometric contention of the argument that climate variables do not reflect the role of climate per se is that some or all of these variables are correlated with the error terms in the regression. This is a classic econometric problem that may be caused by omitted variables, measurement errors, or other factors. The standard solution is to treat the suspect climate variables as endogenous and look for instruments that are correlated with the climate variables but not with the error term—see, for example, Cameron and Trivedi (2006, chapter 4) or Baum (2005, chapter 8). It is not easy to find suitable instruments for all of the climate variables, especially as a group, since physical characteristics of countries are included in the infrastructure demand equations. We have investigated a range of potential instruments, such as the absolute value of latitude (the best instrument for temperature); internal renewable water resources; numbers of bird, mammal, and plant species per sq km; percentage covered by water and snow/ice; and spatially weighted physical characteristics for neighboring countries. These instruments perform reasonably well for mean temperature and temperature range (both population-weighted and inverse population-weighted) on their own. In these cases, the use of instrumental variables does not alter our conclusions. The variables turn out to be weak instruments for total precipitation and precipitation range on their own or for all climate variables together, but no one has seriously proposed that either total precipitation or precipitation range act as proxies for other influences on infrastructure demand. Finally, the analysis using instrumental variables consistently fails to reject the hypothesis that the climate variables—either individually or as a group—can be treated as exogenous; that is, that the correlation between the climate variables and the error term is zero.

d. A final possibility is that climate variables act as instruments for governance variables. One problem is that governance ratings change over time, whereas the climate variables are constant. To get around this, we have computed country averages for the years for which data is available and constructed the correlation matrices for both population-weighted and inverse population-weighted climate variables. Population-weighted mean temperature and precipitation range would be the best instruments, as they have simple correlations of -0.41 to -0.49 for the main WGI governance variables—notably government effectiveness, regulatory quality, and rule of law. Population-weighted precipitation and temperature range have very low correlations with the governance variables, and the correlations for the inverse population-weighted variables are significantly worse than for the population-weighted variables. With squared correlations of 0.2 or less, climate variables would have high standard errors if they were acting as instruments for governance—roughly 5 times the true standard errors for the governance variables—which is difficult to reconcile with the relatively high t-ratios actually obtained. Further, including governance variables in the tests reported below may reduce or increase the F-values for the joint tests on the sets of climate variables, but it does not alter the inference. Overall, our results provide little support for this interpretation.

It is not possible to prove a negative. Our analysis cannot demonstrate conclusively that the coefficients on our climate variables reflect the effects of climate per se rather than the indirect influence of other, non-climate, factors. Nonetheless, we would argue that the cumulative weight of evidence is strong enough to shift the burden of proof. A key point is that the influence of climate in our infrastructure equations rarely depends upon a single climate variable on its own, whereas arguments about the role of climate as a proxy or instrument for other factors focus almost exclusively on mean temperature. There is even less reason to believe that inverse population-weighted climate variables act in this way, since by definition these reflect climate patterns in areas where people do not live and have not lived in large numbers.[15] Hence, after extensive and careful investigation, we conclude that the evidence supports the view that climate does and will have a significant influence on future demand for infrastructure. In reaching this conclusion, we have been particularly strict when considering the inclusion of mean temperature (population-weighted and inverse population-weighted) in our projection models, so there has been a bias in favor of omitting these variables unless there was unambiguous support for retaining them. On that basis, we believe it is reasonable to estimate the Delta-Q component of adaptation over the full period from 2010 to 2050 on the basis of the demand projections generated by our equations.

The primary investigation of alternative specifications is carried out using pooled OLS with Driscoll-Kraay standard errors, which allow for a general pattern of spatial dependence between countries (Driscoll and Kraay 1998; Hoechle 2007).[16] In the case of the proportions of the population covered by electricity, water, and sewer networks, the dependent variable is the logit of the relevant shares in order to translate values between 0 and 1 to the entire real line. It is necessary to censor values that are reported as either 0 or 1 in order to avoid degeneracy. Thus, the minimum and maximum values correspond to shares of 0.001 and 0.999, as the shares are reported to the nearest 0.1 of a percentage point. A panel tobit model has been used to estimate the demand equations for coverage rates for which a significant fraction of observations are censored from above with the upper limit equal to logit (0.999).

In addition to climate variables, the explanatory variables in the base models are:

- Log of population
- Logs of GDP per person at 2005 PPP, country size, and urban population as percentage of total population plus quadratic terms in these variables
- Log of a cross-country building cost index with the U.S.=1.0
- Logs of the proportions of land area that are desert, arid, semi-arid, steep, very steep, and have no soil constraints for agriculture—obtained from FAO's Terrastat database
- Logs of the birth rate and infant mortality for 1950-54
- Dummy variables for World Bank regions.

The last two groups of variables are retained in all models. Tests for the inclusion of non-climate and climate variables are performed separately. At the first stage, the non-climate variables are tested for significance in a model containing the seven climate variables—pop and ipop variants other than temperature range. After dropping non-climate variables that do not have significant coefficients, tests on the hypotheses that the coefficients for (a) the population-weighted climate variables, (b) the inverse population-weighted climate variables, and (c) all climate variables are all equal to zero are carried out. If one or more of these hypotheses are rejected, the set of climate variables included in the model is reduced by first dropping either the pop or the ipop variants and then those variables within each category that do not have significant coefficients. Finally, interactions with GDP and urbanization are tested for the climate variables that have been retained.

Finally, we have used total, urban, or rural population weights (as appropriate) in estimating equations for which the dependent variable is the log or logit of an infrastructure indicator per person or per household; for example, municipal industrial water use per person,

15 The absolute values of the correlation coefficients between the logs of similarly weighted climate variables are less than 0.66 across our sample of countries, with the sole exception of total precipitation and precipitation range (see Table 1). Both temperature and precipitation are negatively correlated with temperature range. The correlation coefficients between population-weighted and inverse population-weighted variables range from 0.78 to 0.83, with the exception of temperature range, for which the value is 0.94. In view of this last correlation, we have excluded the inverse-population weighted temperature range from the analysis.

16 Driscoll-Kraay standard errors are robust to panel heteroscedasticity and temporal autocorrelation as well as spatial interdependence. The estimation is carried out using Hoechle's xtscc procedure in Stata, which generalizes the Driscoll-Kraay estimator to allow for unbalanced panels. There is an important feature of the Driscoll-Kraay/Hoechle procedure that needs to be kept in mind. The method relies upon the derivation of a robust covariance matrix for a sequence of cross-sectional averages. The panels used for our analysis of some categories of infrastructure are very unbalanced and do not span continuous periods of time. Nonetheless, cross-sectional averages can be calculated for more than 25 years. The sample of countries in each cross-sectional average differs, but this is consistent with the way in which the covariance estimator is specified. Thus, even though the Driscoll-Kraay analysis relies upon asymptotics as $T\rightarrow\infty$, the nature of our data is consistent with its basic requirements.

average household size, or the percentages of households connected to electricity, water, or sewer networks. In all cases, the weights are normalized to sum to the number of observations used for the analysis.

5. THE EFFECTS OF CLIMATE ON DEMAND FOR INFRASTRUCTURE

Electricity generating capacity. Model (1) in Table 2 shows that the tests for the joint significance of the climate variables reject the hypothesis of zero coefficients decisively for both the population-weighted and the inverse population-weighted climate variables. The rejection of the hypothesis of zero coefficients is particularly strong for the inverse-population weighted climate variables; this is reinforced by the higher values of the t-ratios for these coefficients. The only climate variable with a coefficient that is not significantly different from zero is population-weighted mean temperature. On the other hand, both temperature range and inverse population-weighted mean temperature have coefficients that are highly significant. The signs of the coefficients differ, but these variables are negatively correlated (see Table 1) so that warmer countries tend to have less generating capacity, holding other factors constant.

TABLE 2. PROJECTION EQUATIONS FOR ELECTRICITY GENERATING CAPACITY, FIXED TELEPHONE LINES, AND ELECTRICITY NETWORK COVERAGE

	Ln(Generating capacity)		*Ln(Fixed telephone lines)*		*Logit(Urban electricity coverage)*		*Logit(Rural electricity coverage)*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Population)	0.954***	0.959***	1.088***	1.081***	0.729**	0.641**	1.882***	1.750***
	(0.028)	(0.021)	(0.033)	(0.030)	(0.222)	(0.217)	(0.150)	(0.152)
Ln(GDP per person)	0.975***	0.926***	0.618***	0.608***	3.706***	3.703***	5.909***	6.496***
	(0.141)	(0.129)	(0.024)	(0.016)	(0.562)	(0.556)	(0.587)	(0.642)
Ln(Country size)	1.111***	1.034***	-0.159***	-0.150***			4.454***	5.208***
	(0.137)	(0.117)	(0.026)	(0.026)			(0.630)	(0.697)
Ln(% urban)	2.936***	4.248***	2.084***	1.340	-10.59***	-10.43***	-7.703***	8.478
	(0.563)	(0.711)	(0.474)	(1.593)	(3.141)	(3.122)	(1.554)	(4.349)
Ln(% urban) squared	0.324***	0.309***						
	(0.050)	(0.044)						
Ln(GDP per person) *	-0.115***	-0.108***					-0.621***	-0.714***
Ln(Country size)	(0.014)	(0.012)					(0.070)	(0.078)
Ln(GDP per person) *	-0.239***	-0.226***	-0.203**	-0.191**	1.683***	1.660***	0.627**	0.776***
Ln(% urban)	(0.056)	(0.060)	(0.066)	(0.062)	(0.428)	(0.427)	(0.211)	(0.218)
Ln(Country size) *	0.131***	0.106***					1.001***	1.091***
Ln(% urban)	(0.027)	(0.026)					(0.136)	(0.140)

(*continued*)

TABLE 2. PROJECTION EQUATIONS FOR ELECTRICITY GENERATING CAPACITY, FIXED TELEPHONE LINES, AND ELECTRICITY NETWORK COVERAGE (*continued*)

	Ln(Generating capacity)		*Ln(Fixed telephone lines)*		*Logit(Urban electricity coverage)*		*Logit(Rural electricity coverage)*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Building cost)			-1.878***	-1.712***	21.44**	18.21**	17.94***	14.30***
			(0.289)	(0.284)	(6.636)	(5.967)	(3.502)	(3.348)
Ln(% desert)	0.0276***	0.0278***	0.0250***	0.0351***				
	(0.004)	(0.005)	(0.005)	(0.007)				
Ln(% semi-arid)	-0.0378***	-0.0297**	0.0296***	0.0307***				
	(0.011)	(0.011)	(0.004)	(0.004)				
Ln(% steep land)			-0.107***	-0.111***			-1.509***	-0.321
			(0.008)	(0.012)			(0.413)	(0.350)
Ln(% very steep land)	0.0947***	0.0792***	0.0647***	0.0647***				
	(0.008)	(0.007)	(0.004)	(0.004)				
Ln(% no soil constraint)	-0.0522***	-0.0414***	0.0365***	0.0346***			-0.805***	-1.146***
	(0.010)	(0.008)	(0.006)	(0.007)			(0.167)	(0.142)
Ln(Temperature - pop)	-0.837		-2.158***	-2.620***	-5.626		-7.115*	
	(0.480)		(0.202)	(0.376)	(6.088)		(3.084)	
Ln(Precipitation - pop)	0.395***	0.152***	-0.001		-3.175**	-3.884***	-1.541*	
	(0.069)	(0.040)	(0.085)		(1.224)	(1.098)	(0.767)	
Ln(Temp range - pop)	0.313**	0.386***	-0.250**	0.144*	-6.061**	-3.735**	-4.629***	
	(0.103)	(0.074)	(0.090)	(0.067)	(1.866)	(1.228)	(1.119)	
Ln(Precip range - pop)	-0.431***	-0.272***	-0.169**	-0.0449**	3.574**	3.799***	2.094**	1.388***
	(0.055)	(0.052)	(0.065)	(0.017)	(1.342)	(1.055)	(0.756)	(0.310)
Ln(Temperature - ipop)	-1.057***	-1.447***	-0.388***	0.305***	-0.203		-10.53***	-13.65***
	(0.137)	(0.125)	(0.111)	(0.068)	(2.396)		(1.418)	(1.946)
Ln(Precipitation - ipop)	-0.272***	-0.269***	-0.149		-1.771		-1.270**	
	(0.045)	(0.036)	(0.098)		(0.997)		(0.490)	
Ln(Precip range - ipop)	0.479***	0.468***	0.240**	0.0542*	1.018		1.012*	
	(0.055)	(0.048)	(0.077)	(0.025)	(1.001)		(0.509)	
Ln(% urban) *				-1.006**				
Ln(Temperature - pop)				(0.363)				

TABLE 2. PROJECTION EQUATIONS FOR ELECTRICITY GENERATING CAPACITY, FIXED TELEPHONE LINES, AND ELECTRICITY NETWORK COVERAGE (*continued*)

	Ln(Generating capacity)		*Ln(Fixed telephone lines)*		*Logit(Urban electricity coverage)*		*Logit(Rural electricity coverage)*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(% urban) *		-0.388***						
Ln(Precipitation - pop)		(0.050)						
Ln(% urban) *				0.328***				
Ln(Temp range - pop)				(0.070)				
Ln(% urban) *		0.270***		0.139***				
Ln(Precip range - pop)		(0.066)		(0.031)				
Ln(% urban) *				0.862***				-4.295***
Ln(Temperature - ipop)				(0.102)				(1.151)
Ln(% urban) *				-0.0749***				
Ln(Precip range - ipop)				(0.009)				
Model	POLS	POLS	POLS	POLS	Tobit	Tobit	Tobit	Tobit
Observations	6027	6027	5130	5130	906	906	853	853
Number of countries	165	165	186	186	130	130	127	127
R-squared	0.923	0.924	0.938	0.939				
Log-likelihood					-250.6	-253.2	-436.6	-438.4
DF	26	27	25	28	19	15	24	20
No of censored obs					716	716	661	661
P-value for all climate variables = 0	0.000		0.000		0.008		0.000	
P-value for pop climate variables = 0	0.000		0.000		0.005		0.000	
P-value for ipop climate variables = 0	0.000		0.000		0.167		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

Overall, however, temperature and temperature range are less important influences on the amount of generating capacity than precipitation and precipitation range together with their interactions with urbanization. There are various mechanisms by which precipitation may affect installed capacity. One factor is the role of hydro power in total electricity supply, since utilization factors tend to be lower for hydro plants. Another is the role of pumped irrigation systems and similar influences on patterns of electricity demand in countries with high interseasonal variations in rainfall. Even though the absolute values of the coefficients for precipitation and precipitation range are smaller than the equivalent coefficients for temperature, these variables have an important effect in the calculation of the Delta-Q changes because the distributions of changes in total precipitation and precipitation range are much more dispersed and much larger relative to their historic values than are the equivalent distributions for temperature.

Fixed telephone lines. The projection equations for fixed telephone lines are reported as Models (3) & (4) in Table 2. Again, the hypotheses of zero coefficients for climate variables are decisively rejected, particularly for the population-weighted variables, with mean temperature, temperature range, and precipitation range all having significant coefficients. There are strong interactions with urbanization, so that the impact of climate change on demand for telephones varies markedly both within and across country classes.

Electricity network coverage. Models (5) through (8) in Table 2 show the estimated equations for the logits of electricity coverage for urban and rural households weighted by the relevant populations in 2005.[17] Panel tobit models are used with an upper censoring value corresponding to a coverage of 99.9 percent. Since the majority of observations are censored, the number of exogenous variables is reduced in each equation by much more than for electricity generating capacity. Nonetheless, population-weighted precipitation, precipitation range, and temperature range clearly warrant inclusion in the equation for urban coverage. For rural coverage, population-weighted precipitation range and inverse population-weighted temperature—on its own and interacted with urbanization—are the key climate variables. The chi-square statistic for the test of zero influence of the temperature variables is 59.7, so that these cannot be excluded.

Water use. The dependent variables for water use are the logs of water abstractions per person for municipal and industrial use, which are derived from FAO data. This includes water that is lost in treatment and in water supply networks. Models (1) and (2) in Table 3 summarize the results of the econometric analysis for municipal water use per person. In this case, the tests for the joint significance of the climate variables reject the hypothesis of zero coefficients decisively for the population-weighted variables, but not for the inverse population-weighted variables. The best specification includes population-weighted precipitation and precipitation range. Another point to note is the quadratic in GDP per person. The results seem to be intuitively reasonable, reflecting rainfall patterns where people live and the effect of changes in GDP on water use. The quadratic terms in GDP per person imply that water consumption per person reaches a peak at an income of about $12,000 per capita in 2005 PPP, and falls gradually as countries get richer beyond this point.

Models (3) and (4) in Table 3 summarize the results for industrial water use per person. In this case, the tests reject the hypotheses that the population-weighted and/or inverse population-weighted climate variables have zero coefficients. The detailed investigation identifies population-weighted temperature range and precipitation range plus inverse population-weighted precipitation and precipitation range as having significant coefficients. There are significant interactions between the inverse-population weighted climate variables and GDP per person with urbanization. Use of water in industry is a derived demand, so the influence of climate variables operates through the scale and location of food processing and similar resource-based industries. Hence, it is climate conditions in rural and thinly populated areas that have a significant influence.

Water and sewer connections. Table 4 summarizes the results for coverage rates of piped water supply and

17 For the purpose of projecting the total numbers of connections, it is necessary to allow for non-household connections. We have assumed that the total numbers of electricity connections are 108 percent of the numbers of households connected to the network. This multiplier reflects the typical ratio for upper-middle and high-income countries.

TABLE 3. PROJECTION EQUATIONS FOR MUNICIPAL AND INDUSTRIAL WATER DEMAND

	Ln(Municipal water use per person)		*Ln(Industrial water use per person)*	
Variables	(1)	(2)	(3)	(4)
Ln(GDP per person)	2.159**	2.000**	3.455**	2.953*
	(0.679)	(0.632)	(1.073)	(1.197)
Ln(Country size)				
Ln(% urban)	0.530***	0.559***		
	(0.071)	(0.067)		
Ln(GDP per person) squared	-0.115**	-0.105**	-0.191**	-0.219***
	(0.039)	(0.036)	(0.064)	(0.064)
Ln(Building cost)	-2.477***	-2.342*		
	(0.662)	(0.904)		
Ln(% steep land)			0.970***	0.943***
			(0.124)	(0.100)
Ln(% very steep land)	0.152***	0.156***	-0.225***	-0.183**
	(0.023)	(0.032)	(0.054)	(0.059)
Ln(% no soil constraint)			-0.265***	-0.156***
			(0.040)	(0.027)
Ln(Temperature - pop)	0.923*		-0.027	
	(0.391)		(1.219)	
Ln(Precipitation - pop)	-0.150	-0.306***	0.456	
	(0.173)	(0.087)	(0.354)	
Ln(Temp range - pop)	0.459**		2.091***	2.003***
	(0.163)		(0.294)	(0.221)
Ln(Precip range - pop)	0.205	0.367***	-0.819*	-0.594***
	(0.175)	(0.103)	(0.323)	(0.127)
Ln(Temperature - ipop)	0.079		-0.842	
	(0.239)		(0.592)	
Ln(Precipitation - ipop)	0.102		-0.512*	-5.318***
	(0.081)		(0.240)	(0.836)
Ln(Precip range - ipop)	-0.054		0.902**	5.682***
	(0.103)		(0.287)	(0.931)
Ln(GDP per person) *				0.577***
Ln(Precipitation - ipop)				(0.099)
Ln(GDP per person) *				-0.577***
Ln(Precip range - ipop)				(0.107)
Model	POLS	POLS	POLS	POLS
Observations	368	368	337	337
Number of countries	161	161	158	158

(*continued*)

TABLE 3. PROJECTION EQUATIONS FOR MUNICIPAL AND INDUSTRIAL WATER DEMAND (*continued*)

	Ln(Municipal water use per person)		*Ln(Industrial water use per person)*	
Variables	(1)	(2)	(3)	(4)
R-squared	0.980	0.979	0.954	0.955
Log-likelihood				
DF	19	14	19	18
No of censored obs				
P-value for all climate variables = 0	0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000	
P-value for ipop climate variables = 0	0.087		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

sewer networks in urban and rural areas. Models (1) to (6) are based upon panel tobit estimation, allowing for the upper censoring of countries with reported coverage of 99.9 percent or higher. In general, population-weighted climate variables have a significant influence on coverage rates in urban areas, while inverse population-weighted climate variables are more important in rural areas. The only exception is rural water supply, for which both sets of climate variables are significant. Interactions with GDP per person and urbanization are not significant. Since coverage rates for piped water supply are close to or equal to 99.9 percent in high income countries, changes in climate variables will not have any effect on costs of adaptation in many countries. However, changes in average temperature—and precipitation for rural households—may affect the numbers of households connected to collective sewer systems.[18]

For the purpose of costing wastewater treatment, we have assumed that the BOD/COD concentration and other characteristics of sewage handled by wastewater treatment plants correspond to typical values for municipal wastewater. This implies that industries will be expected to process wastewater with high concentrations of industrial pollutants. Further, it is assumed that wastewater treatment plants are scaled to process 80 percent of the volume of water treated by water treatment plants, allowing for network losses and wastewater that is not discharged to sewers.

Roads. Table 5 shows equations for the total length of roads (both paved and unpaved) and for the logit of the share of paved roads in total road length, weighted by total road length in the latter case. The key climate variables affecting the length of roads are temperature and precipitation range—both population-weighted and inverse population-weighted—plus population-weighted temperature range. There are strong interactions with GDP per person for temperature and precipitation

18 It should be emphasized that this is not a matter of whether households have access to some form of adequate sanitation. The dependent variable is the proportion of households that are connected to community sewers, rather than relying upon septic tanks or equivalent individual arrangements. Community sewers are more expensive to construct and the wastewater that is collected must be treated, so costs of adaptation arise from shifts to or away from reliance on community sewers. Again, we have allowed for non-household connections by assuming that the total numbers of water supply and sewer connection are 10 percent higher than the numbers of household connections, based on typical ratios for middle-income countries.

TABLE 4. PROJECTION EQUATIONS FOR WATER AND SEWER NETWORKS

	Logit(Urban water coverage)		*Logit(Rural water coverage)*		*Logit(Urban sewer coverage)*		*Logit(Rural water coverage)*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Population)	0.353**	0.300*	0.513***	0.488***	0.357**	0.278*	0.765***	0.783***
	(0.127)	(0.118)	(0.113)	(0.113)	(0.119)	(0.117)	(0.149)	(0.230)
Ln(GDP per person)	0.889***	0.901***	0.430	0.647	2.576***	2.629***	1.405***	1.407***
	(0.150)	(0.148)	(0.826)	(0.824)	(0.348)	(0.350)	(0.346)	(0.335)
Ln(Country size)	-0.580***	-0.539***	1.327***	1.439***	2.035***	2.161***	-0.636***	-0.635***
	(0.112)	(0.095)	(0.318)	(0.314)	(0.407)	(0.405)	(0.102)	(0.175)
Ln(% urban)	-3.744***	-3.797***	1.388***	1.371***			1.247***	1.226***
	(0.995)	(0.982)	(0.230)	(0.229)			(0.339)	(0.268)
Ln(GDP per person) squared			0.157**	0.149**				
			(0.053)	(0.053)				
Ln(GDP per person) *			-0.282***	-0.293***	-0.276***	-0.285***		
Ln(Country size)			(0.035)	(0.034)	(0.041)	(0.042)		
Ln(GDP per person) *	0.451***	0.462***						
Ln(% urban)	(0.131)	(0.130)						
Ln(Building cost)	-7.790**	-9.089***					13.91**	14.16*
	(2.878)	(2.607)					(4.162)	(5.822)
Ln(% desert)	-0.188*	-0.201***						
	(0.080)	(0.051)						
Ln(% arid land)					-0.421***	-0.295***	-0.254***	-0.266***
					(0.082)	(0.073)	(0.053)	(0.072)
Ln(% semi-arid land)			0.141*	0.162*	0.375***	0.449***		
			(0.064)	(0.063)	(0.075)	(0.074)		
Ln(% no soil constraint)					-0.282*	-0.422***		
					(0.114)	(0.091)		
Ln(Temperature - pop)	-8.469***	-8.000***	-0.351		-5.950**	-7.603***	0.281	
	(2.303)	(1.352)	(2.406)		(2.128)	(1.452)	(3.102)	
Ln(Precipitation - pop)	-0.262		-1.690**	-1.319***	0.128		0.149	
	(0.530)		(0.570)	(0.214)	(0.529)		(0.625)	
Ln(Temp range - pop)	-0.693		-1.793*	-1.498**	-0.119		-0.023	
	(0.742)		(0.767)	(0.484)	(0.747)		(0.325)	
Ln(Precip range - pop)	-1.184*	-1.500***	0.870		0.288		-0.413	
	(0.517)	(0.238)	(0.593)		(0.531)		(0.823)	
Ln(Temperature - ipop)	-0.761		-6.472***	-6.385***	-1.098		-3.842***	-3.745***
	(1.033)		(0.947)	(0.863)	(0.889)		(0.864)	(0.485)
Ln(Precipitation - ipop)	-0.017		0.131		-0.283		-0.981***	-0.855***
	(0.375)		(0.381)		(0.356)		(0.190)	(0.085)

(*continued*)

TABLE 4. PROJECTION EQUATIONS FOR WATER AND SEWER NETWORKS (*continued*)

	Logit(Urban water coverage)		*Logit(Rural water coverage)*		*Logit(Urban sewer coverage)*		*Logit(Rural water coverage)*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Precip range - ipop)	-0.084		-0.486		-0.429		0.255	
	(0.416)		(0.425)		(0.430)		(0.269)	
Model	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit	POLS	POLS
Observations	582	582	547	547	318	318	272	272
Number of countries	157	157	155	155	140	140	124	124
R-squared							0.901	0.901
Log-likelihood	-452.1	-452.9	-461.5	-464.7	-327.0	-335.1		
DF	21	16	21	17	21	15	20	15
No of censored obs	94	94	36	36	10	10		
P-value for all climate variables = 0	0.000		0.000		0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000		0.024		0.021	
P-value for ipop climate variables = 0	0.854		0.001		0.002		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

TABLE 5. PROJECTION EQUATIONS FOR ROADS

	Ln(Total road length)		Logit(Share of paved roads)	
Variables	(1)	(2)	(3)	(4)
Ln(Population)	0.584***	0.590***	0.599***	0.668***
	(0.004)	(0.005)	(0.057)	(0.064)
Ln(GDP per person)	-0.042	2.070***	1.980***	8.010***
	(0.034)	(0.098)	(0.094)	(0.781)
Ln(Country size)	-0.0931*	-0.007	3.645***	0.081
	(0.045)	(0.029)	(0.473)	(0.300)
Ln(% urban)	0.395***	0.786***	-2.207***	-0.845
	(0.069)	(0.074)	(0.389)	(0.520)
Ln(Country size) squared	0.0166***	0.0175***	-0.108***	-0.0668***
	(0.002)	(0.001)	(0.019)	(0.013)
Ln(% urban) squared	-0.155***	-0.0581***		
	(0.015)	(0.010)		

(*continued*)

TABLE 5. PROJECTION EQUATIONS FOR ROADS (*continued*)

	Ln(Total road length)		Logit(Share of paved roads)	
Variables	(1)	(2)	(3)	(4)
Ln(GDP per person) *	0.0331***	0.0217***	-0.316***	0.010
Ln(Country size)	(0.003)	(0.002)	(0.023)	(0.023)
Ln(GDP per person) *	-0.105***	-0.199***		
Ln(% urban)	(0.006)	(0.012)		
Ln(Country size) *			0.434***	0.036
Ln(% urban)			(0.053)	(0.037)
Ln(Building cost)			-11.84***	-9.597***
			(0.778)	(0.527)
Ln(% desert)	0.0347***	0.0546***	-0.157***	-0.232***
	(0.009)	(0.006)	(0.025)	(0.033)
Ln(% arid)			0.396***	0.371***
			(0.041)	(0.065)
Ln(% semi-arid)	-0.0492***	-0.0503***		
	(0.005)	(0.004)		
Ln(% steep land)	0.100***	0.0660***		
	(0.013)	(0.011)		
Ln(% very steep land)	-0.0245***	-0.0111***	0.196***	0.174***
	(0.004)	(0.002)	(0.040)	(0.045)
Ln(% no soil constraint)	0.0279***	0.0402***		
	(0.006)	(0.005)		
Ln(Temperature - pop)	-1.267***	1.589***	2.041	
	(0.190)	(0.424)	(1.121)	
Ln(Precipitation - pop)	0.017		0.262	
	(0.030)		(0.242)	
Ln(Temp range - pop)	-0.108**	-0.208***	-2.074***	16.46***
	(0.038)	(0.042)	(0.106)	(1.595)
Ln(Precip range - pop)	-0.170**	-0.154***	-2.099***	0.663*
	(0.055)	(0.028)	(0.319)	(0.315)
Ln(Temperature - ipop)	0.593***	0.684***	-2.213***	-1.829***
	(0.141)	(0.145)	(0.530)	(0.256)
Ln(Precipitation - ipop)	0.039		-0.646***	
	(0.069)		(0.176)	
Ln(Precip range - ipop)	0.156*	1.334***	0.976***	
	(0.060)	(0.070)	(0.071)	
Ln(% urban) *		0.110***		
Ln(Precip range - pop)		(0.011)		
Ln(GDP per person) *		-0.373***		
Ln(Temperature - pop)		(0.025)		

(*continued*)

TABLE 5. PROJECTION EQUATIONS FOR ROADS (*continued*)

	Ln(Total road length)		Logit(Share of paved roads)	
Variables	(1)	(2)	(3)	(4)
Ln(GDP per person) *				-2.150***
Ln(Temp range - pop)				(0.192)
Ln(GDP per person) *				-0.190***
Ln(Precip range - pop)				(0.038)
Ln(GDP per person) *		-0.127***		
Ln(Precip range - ipop)		(0.008)		
Model	POLS	POLS	POLS	POLS
Observations	2040	2040	1790	1790
Number of countries	182	182	179	179
R-squared	0.922	0.926	0.816	0.822
Log-likelihood				
DF	27	28	25	23
No of censored obs				
P-value for all climate variables = 0	0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000	
P-value for ipop climate variables = 0	0.000		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

range and with urbanization for precipitation range. These climate variables are directly linked to the cost of building and maintaining roads—temperature is particularly important for paved roads subject to heavy use, while temperature and precipitation ranges affect the capital and maintenance costs of both paved and unpaved roads. The fact that both population-weighted and inverse-population weighted climate variables are significant reflects the impact of climate on all types of roads—rural, urban, and national. It is likely that climate may also play a role through the structure of the economy—for example, the nature and role of agricultural production—and through geographical patterns of economic development.

The share of paved roads in total road length is influenced by the same variables and their interactions with GDP per person. In particular, higher temperatures in rural areas—that is, inverse population-weighted temperature—lead to a lower share of paved roads, which is exactly what one would expect in view of the higher costs of construction and maintenance for rural paved roads associated with higher temperatures.

Other transport. Table 6 shows the projection equations for rail track length, aircraft movements, and container traffic handled by ports. The last two are indicators used in estimating investments in airports and sea/river ports. With one exception, the tests reject the hypothesis of zero coefficients for all climate variables decisively. The exception is for inverse population-weighted climate variables in the rail equation. The primary climate influences are:

TABLE 6. PROJECTION EQUATIONS FOR OTHER TRANSPORT

	Ln(Rail track length)		*Ln(Aircraft movements)*		*Ln(Container traffic)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln(Population)	0.484***	0.472***	0.540***	0.540***	0.649***	0.649***
	(0.043)	(0.041)	(0.035)	(0.032)	(0.034)	(0.023)
Ln(GDP per person)	0.259***	0.971	0.710***	0.692***	0.005	-2.830***
	(0.053)	(0.741)	(0.065)	(0.066)	(0.074)	(0.748)
Ln(Country size)	0.425***	0.405***	-0.184***	-0.167***	-2.751***	-3.495***
	(0.076)	(0.049)	(0.030)	(0.030)	(0.195)	(0.363)
Ln(% urban)	-0.315	-0.215	-0.376**	2.202***	3.989***	-0.071
	(0.172)	(0.146)	(0.143)	(0.571)	(0.389)	(1.116)
Ln(Country size) squared			0.0337***	0.0325***	0.0299***	0.0278***
			(0.003)	(0.003)	(0.003)	(0.003)
Ln(% urban) squared			-0.112*		1.090***	1.563***
			(0.047)		(0.168)	(0.171)
Ln(GDP per person) *					0.222***	0.302***
Ln(Country size)					(0.015)	(0.034)
Ln(Country size) *					-0.507***	-0.513***
Ln(% urban)					(0.021)	(0.026)
Ln(Building cost)	-3.062***	-2.936***				
	(0.349)	(0.339)				
Ln(% desert)			0.0862***	0.0728***	0.266***	0.223***
			(0.021)	(0.020)	(0.009)	(0.015)
Ln(% arid)					-0.333***	-0.363***
					(0.012)	(0.011)
Ln(% semi-arid)					0.0404***	0.0710***
					(0.006)	(0.004)
Ln(% steep land)			-0.132***	-0.144***		
			(0.029)	(0.032)		
Ln(% very steep land)			0.0743***	0.0819***		
			(0.010)	(0.011)		
Ln(Temperature - pop)	-2.235***	3.225*	-0.466		0.712*	
	(0.660)	(1.288)	(0.334)		(0.307)	
Ln(Precipitation - pop)	0.362***	-1.378***	-0.396***	-0.351***	0.591***	0.909***
	(0.035)	(0.153)	(0.102)	(0.080)	(0.140)	(0.124)
Ln(Temp range - pop)	0.939***	-0.797	-1.038***	-1.400***	0.232	
	(0.183)	(0.512)	(0.131)	(0.111)	(0.170)	
Ln(Precip range - pop)	-0.175		0.373***	0.313***	0.035	
	(0.123)		(0.053)	(0.044)	(0.079)	
Ln(Temperature - ipop)	0.814		-1.005***	-1.084***	-0.906***	-6.590***
	(0.745)		(0.114)	(0.091)	(0.093)	(1.305)

(*continued*)

TABLE 6. PROJECTION EQUATIONS FOR OTHER TRANSPORT (*continued*)

	Ln(Rail track length)		*Ln(Aircraft movements)*		*Ln(Container traffic)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln(Precipitation - ipop)	0.149		0.326***	0.026	0.429***	0.261***
	(0.133)		(0.046)	(0.072)	(0.075)	(0.051)
Ln(Precip range - ipop)	-0.217		-0.183***	0.060	-0.457***	-0.326***
	(0.174)		(0.041)	(0.059)	(0.034)	(0.058)
Ln(% urban) *						0.707***
Ln(Precipitation - pop)						(0.163)
Ln(% urban) *				-0.508***		
Ln(Temp range - pop)				(0.074)		
Ln(% urban) *				-0.354***		
Ln(Precipitation - ipop)				(0.089)		
Ln(% urban) *				0.324***		
Ln(Precip range - ipop)				(0.058)		
Ln(GDP per person) *		-0.580***				
Ln(Temperature - pop)		(0.156)				
Ln(GDP per person) *		0.167***				
Ln(Precipitation - pop)		(0.014)				
Ln(GDP per person) *		0.159**				
Ln(Temp range - pop)		(0.051)				
Ln(GDP per person) *						0.612***
Ln(Temperature - ipop)						(0.139)
Model	POLS	POLS	POLS	POLS	POLS	POLS
Observations	1969	1969	5040	5040	407	407
Number of countries	133	133	175	175	69	69
R-squared	0.741	0.740	0.831	0.833	0.805	0.822
Log-likelihood						
DF	19	18	23	24	25	24
No of censored obs						
P-value for all climate variables = 0	0.000		0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000		0.000	
P-value for ipop climate variables = 0	0.040		0.000		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

a. Rail length—temperature, precipitation, and temperature range, both on their own and interacted with GDP per person

b. Aircraft movements—all climate variables other than population-weighted temperature plus interactions with urbanization

c. Container traffic—both precipitation variables, inverse population-weighted temperature, and precipitation plus interactions with urbanization and GDP per person.

In these cases, there is no easy explanation for the results since it is clear that there are multiple influences on the indicators. For example, the number of aircraft movement will be affected by factors such as the amount and distribution of tourism (both internal and external), the dispersion and nature of natural-resource based industries, and the availability of alternative methods of transport.

Health care. Our analysis of adaptation costs relies upon two health care inputs—the numbers of hospital beds and physicians —as indicators used in assessing the baseline cost of health infrastructure (hospitals and clinics) and the impact of climate change. The projection equations are shown in Models (1) through (4) of Table 7. In addition, Models (5) and (6) report equations for one important indicator of health outcomes—the log of the infant mortality rate.

TABLE 7. PROJECTION EQUATIONS FOR HEALTH

	Ln(No of hospital beds)		*Ln(No of doctors)*		*Ln(Infant mortality rate)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln(Population 0-14)	0.283**	0.323***	-0.520***	-0.558**	1.423***	1.444***
	(0.099)	(0.060)	(0.135)	(0.187)	(0.116)	(0.129)
Ln(Population 15-64)	0.881***	0.736***	1.300***	1.196***	-0.982***	-0.964***
	(0.131)	(0.064)	(0.120)	(0.182)	(0.132)	(0.143)
Ln(Population 65+)	-0.224***	-0.128***	0.275***	0.391***	-0.475***	-0.508***
	(0.032)	(0.023)	(0.045)	(0.034)	(0.035)	(0.033)
Ln(GDP per person)	1.721***	-2.680***	0.246**	-4.951***	0.928*	0.947*
	(0.327)	(0.605)	(0.080)	(0.589)	(0.390)	(0.384)
Ln(Country size)	-0.155***	-0.0984***	0.364***	0.147**	0.105***	0.109***
	(0.021)	(0.021)	(0.106)	(0.046)	(0.031)	(0.031)
Ln(% urban)	-0.094		1.077***	1.301***	-0.165***	1.738**
	(0.072)		(0.211)	(0.162)	(0.031)	(0.584)
Ln(GDP per person) squared	-0.100***	-0.0853***			-0.0661**	-0.0661**
	(0.019)	(0.010)			(0.023)	(0.023)
Ln(Country size) squared	0.0173***	0.0124***			0.0111***	0.0116***
	(0.002)	(0.001)			(0.001)	(0.001)
Ln(GDP per person) *			-0.0454***	-0.0185***	-0.0172***	-0.0186***
Ln(Country size)			(0.011)	(0.004)	(0.004)	(0.004)
Ln(GDP per person) *			-0.118***	-0.130***		
Ln(% urban)			(0.027)	(0.024)		
Ln(Country size) *			0.0966***	0.0642***		
Ln(% urban)			(0.015)	(0.010)		

(*continued*)

TABLE 7. PROJECTION EQUATIONS FOR HEALTH (*continued*)

	Ln(No of hospital beds)		*Ln(No of doctors)*		*Ln(Infant mortality rate)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln(% arid)			0.0627***	0.0462***		
			(0.011)	(0.007)		
Ln(% very steep land)			0.0306***	0.0244***		
			(0.005)	(0.006)		
Ln(Temperature - pop)	-1.275***	-10.13***	-1.512***	-7.442***	0.954***	0.345
	(0.084)	(1.416)	(0.173)	(1.432)	(0.142)	(0.216)
Ln(Precipitation - pop)	-0.275***		-0.357***	-0.244***	0.054	
	(0.079)		(0.040)	(0.031)	(0.047)	
Ln(Temp range - pop)	0.011		-0.037		0.263***	0.203***
	(0.102)		(0.044)		(0.052)	(0.053)
Ln(Precip range - pop)	0.168*		0.0722*		-0.102*	
	(0.080)		(0.035)		(0.049)	
Ln(Temperature - ipop)	0.102		-0.276*	-5.061***	-0.262***	-0.208***
	(0.110)		(0.113)	(1.114)	(0.049)	(0.047)
Ln(Precipitation - ipop)	0.164*	0.0756***	-0.0824*		0.0911**	0.0622**
	(0.079)	(0.021)	(0.039)		(0.034)	(0.020)
Ln(Precip range - ipop)	-0.039		0.104**		-0.028	
	(0.058)		(0.037)		(0.044)	
Ln(% urban) *						-0.463**
Ln(Temperature - pop)						(0.139)
Ln(GDP per person) *		1.022***		0.709***		
Ln(Temperature - pop)		(0.159)		(0.162)		
Ln(GDP per person) *				0.536***		
Ln(Temperature - ipop)				(0.125)		
Model	POLS	POLS	POLS	POLS	POLS	POLS
Observations	1852	1852	2650	2650	2486	2486
Number of countries	177	177	180	180	177	177
R-squared	0.936	0.939	0.950	0.955	0.917	0.917
Log-likelihood						
DF	22	17	25	23	24	22
No of censored obs						
P-value for all climate variables = 0	0.000		0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000		0.000	
P-value for ipop climate variables = 0	0.000		0.000		0.000	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

Again, the hypothesis that climate variables have no effect on either health inputs or health outcomes is consistently rejected at very high confidence levels.

a. Hospital beds—Population-weighted temperature on its own and interacted with GDP per person plus inverse population-weighted precipitation are the key variables in this case. The overall coefficient (elasticity) on mean temperature increases—from -3.07 for a low-income country with a GDP per person of $1,000, to -0.72 for a middle-income country with a GDP of $10,000 per person, and to +0.70 for a high-income country with a GDP of $40,000 per person. Thus, it is easy to be misled by simple assumptions about how climate "ought" to affect investment in healthcare facilities that are based on experience in a narrow range of countries. The coefficient on precipitation is positive but quite small. It is possible that this reflects an increased need for dispersed hospital facilities when communications are subject to disruption caused by high rainfall.

b. Doctors —The results for the number of doctors are similar to those for hospital beds, but the influence of temperature is divided between population and inverse population-weight variables. This seems reasonable since hospitals are invariably located in urban areas, whereas doctors may be more dispersed, though this is not the case in the poorest countries. Again, the interactions with GDP per person mean that the overall coefficients switch from negative to positive at a GDP per person of $12,600 for inverse population-weighted temperature, and at a GDP per person of $36,200 for population-weighted temperature. How this works out country-by-country depends upon the temperature distribution across heavily and thinly populated areas. In this case, the coefficient on precipitation is negative and is linked to the population-weighted variable.

c. Infant-mortality—This is influenced by temperature, including an interaction with urbanization plus temperature range and inverse population-weighted precipitation. The signs of the coefficients on temperature can be misinterpreted. Assuming that temperature increases (or decreases) uniformly throughout a country, the net coefficient on temperature is +0.88 for a country with an urbanization rate of 20 percent, but +0.24 for a country with an urbanization rate of 80 percent. Hence, an increase in mean temperature is likely to increase infant mortality, but by more in low-income countries with low levels of urbanization than in middle- and high-income countries with higher levels of urbanization. These results conform with a priori expectations. In addition, a higher temperature range and higher precipitation in rural areas tend to increase infant mortality, both of which seem reasonable.

Social infrastructure. The number of teachers is used as the indicator for investment in schools, while the number of post offices is used as one indicator for municipal infrastructure. The equations are shown in Table 8. As one would expect, one cannot reject the hypothesis that the inverse population-weighted climate variables have no effect on the number of post offices, which are concentrated in areas of greater population

TABLE 8. PROJECTION EQUATIONS FOR SOCIAL INFRASTRUCTURE

	Ln(No of teachers)		*Ln(No of post offices)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*
Ln(Population 0-14)	0.360***	0.397***	0.276***	0.366***
	(0.062)	(0.074)	(0.065)	(0.060)
Ln(Population 15-64)	0.670***	0.544***	0.363***	0.048
	(0.115)	(0.132)	(0.099)	(0.091)

(*continued*)

TABLE 8. PROJECTION EQUATIONS FOR SOCIAL INFRASTRUCTURE (*continued*)

	Ln(No of teachers)		*Ln(No of post offices)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*
Ln(Population 65+)	-0.059	0.029	0.231***	0.445***
	(0.042)	(0.048)	(0.032)	(0.030)
Ln(Population)				
Ln(GDP per person)	0.0878***	0.0851***	1.977***	-1.124**
	(0.022)	(0.020)	(0.155)	(0.403)
Ln(Country size)	-0.188***	-0.111***	-0.0338***	-0.018
	(0.011)	(0.014)	(0.010)	(0.011)
Ln(% urban)	-0.404***	-3.032***	-2.066***	-2.178***
	(0.064)	(0.429)	(0.097)	(0.078)
Ln(GDP per person) squared			-0.107***	-0.109***
			(0.009)	(0.009)
Ln(Country size) squared	0.00308***	0.00191*	0.0139***	0.0133***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(% urban) squared	-0.222***	-0.185***	-0.641***	-0.701***
	(0.023)	(0.025)	(0.031)	(0.027)
Ln(GDP per person) *	0.0170***	0.0114***		
Ln(Country size)	(0.001)	(0.002)		
Ln(Country size) *			0.0861***	0.0729***
Ln(% urban)			(0.011)	(0.011)
Ln(% desert)			0.0318***	0.013
			(0.007)	(0.007)
Ln(% arid)			-0.121***	-0.0989***
			(0.006)	(0.005)
Ln(% semi-arid)			0.0423***	0.0489***
			(0.006)	(0.007)
Ln(% steep land)			-0.0549***	-0.0488***
			(0.012)	(0.013)
Ln(% very steep land)	0.0167***	0.00934***	0.0827***	0.0667***
	(0.003)	(0.003)	(0.006)	(0.010)
Ln(% no soil constraint)	0.0532***	0.0314***		
	(0.003)	(0.007)		
Ln(Temperature - pop)	-0.923***	-0.694***	-2.167***	-10.35***
	(0.071)	(0.084)	(0.119)	(0.859)
Ln(Precipitation - pop)	-0.130***	-0.289***	-0.173**	0.650***
	(0.027)	(0.017)	(0.059)	(0.084)
Ln(Temp range - pop)	-0.277***	-0.217***	-0.518***	-0.537***
	(0.017)	(0.026)	(0.066)	(0.047)

(*continued*)

TABLE 8. PROJECTION EQUATIONS FOR SOCIAL INFRASTRUCTURE (*continued*)

	Ln(No of teachers)		*Ln(No of post offices)*	
Variables	*(1)*	*(2)*	*(3)*	*(4)*
Ln(Precip range - pop)	-0.125***	0.0871***	-0.058	
	(0.014)	(0.014)	(0.052)	
Ln(Temperature - ipop)	0.222***	0.751***	-0.110	
	(0.046)	(0.056)	(0.178)	
Ln(Precipitation - ipop)	0.041		-0.0824*	
	(0.028)		(0.038)	
Ln(Precip range - ipop)	-0.022		0.068	
	(0.031)		(0.046)	
Ln(% urban) *		-0.444***		
Ln(Precipitation - pop)		(0.043)		
Ln(% urban) *		0.485***		
Ln(Precip range - pop)		(0.036)		
Ln(% urban) *		0.825***		
Ln(Temperature - ipop)		(0.045)		
Ln(GDP per person) *				0.931***
Ln(Temperature - pop)				(0.112)
Ln(GDP per person) *				-0.100***
Ln(Precipitation - pop)				(0.007)
Model	POLS	POLS	POLS	POLS
Observations	950	950	3251	3251
Number of countries	167	167	173	173
R-squared	0.979	0.982	0.909	0.911
Log-likelihood				
DF	25	26	29	27
No of censored obs				
P-value for all climate variables = 0	0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000	
P-value for ipop climate variables = 0	0.000		0.065	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

density. Otherwise the results show a mixture of climate interactions with urbanization for the number of teachers and with GDP per person for post offices. Focusing again on mean temperature in the equation for the number of teachers, the overall coefficients for a uniform increase in temperature are -0.55 for an urbanization rate of 20 percent and -0.02 for an urbanization rate of 80 percent, so the effect of climate on teachers is much larger in low-income and rural countries. This is consistent with the well-established difficulty of equipping and staffing rural schools. Of course, low-income countries today are likely to be much more urban in 2050, so that the cumulative impact of an increase in temperature on the number of teachers will be small even in these cases.

Household size. In several cases, the amount of infrastructure is linked to the projected number of households, so it is necessary to rely upon equations that project the average household size in urban and rural areas. These are shown in Table 9. It seems that climate does affect average household sizes. The primary mechanism is that higher temperatures are associated with larger average sizes for both urban and rural households. There is also a significant but quantitatively small impact of precipitation on rural household size.

6. CALCULATING THE COST OF ADAPTATION

The calculation of the cost of adaptation involves a number of steps. The description that follows focuses on investment or capital costs. A similar process is required to estimate changes in the costs of operation and maintenance, both for the baseline level of infrastructure and for changes in infrastructure resulting from changes in climate conditions.[19]

19 The analysis is formulated in terms of periods that are referred to by the first year in the period—that is,2010–14 is shortened to 2010. No attempt is made to allow for within-period changes in variables. Some of the demographic variables (urbanization and population age structure) used in the projection equations are based on period averages. For other variables, such as income and total population, the added complexity of using period averages outweighs the benefits because the main projection equations are frontier models and may overstate the levels of infrastructure required to meet demand over relatively short periods.

Step 1—Construct baseline projections of infrastructure investment. The projection equations discussed in the previous section are used to construct baseline projections of the efficient stock of infrastructure assets for periods from 2010 to 2050 under the assumption of no climate change. The projections of physical infrastructure demand are based upon standard assumptions about income and population growth, population structure, and urbanization. The value of new investment required for infrastructure type i for country j in period t is obtained by multiplying $\Delta Q_{ijt} = Q_{ijt+1} - Q_{ijt}$ by C_{ij}, the unit cost of infrastructure type i in country j at 2005 prices. The unit costs have been compiled from a large variety of World Bank and other sources. A standardized construction cost index has been used to allow for broad cross-country differences in construction costs, but allowances are also made for location (urban or rural) and other special factors. In addition to new investment, we have estimated the amount of investment that would be required to replace infrastructure assets that reach the end of their economic life. There is no realistic way of modeling the age structure of assets in situ at the beginning of the analysis. Implementing a full vintage model of infrastructure is not sensible given the uncertainty about other parameters in the model. Hence, we have adopted a continuous depreciation assumption—that is, in period t the required replacement investment is $(5/L_i)^*Q_{ijt}$ where L_i is the typical economic life of infrastructure of type i.

Step 2—Add alternative climate scenarios. The data used for the baseline projections is supplemented with projections of the climate variables taken from the climate scenarios that are being used for the whole EACC study. These are constructed as deltas at different dates with respect to the no-climate-change baseline derived from calculations of monthly average, maximum, and minimum temperatures and precipitation. To avoid instability in the projections arising from path-dependency and other effects, the climate variables for 2010 are 20-year averages centered on 2010. These are computed for 2010, 2030, … and then interpolated to give the projections for the 5-year periods.

Step 3—Project infrastructure quantities under the alternative climate scenarios. This is similar to the projection of baseline infrastructure quantities in Step 1, but using the climate variables for the alternative climate scenarios.

TABLE 9. PROJECTION EQUATIONS FOR AVERAGE HOUSEHOLD SIZE

	Ln(Urban household size)		Ln(Rural household size)	
Variables	(1)	(2)	(3)	(4)
Ln(Population 0-14)	0.295***	0.353***	0.285***	0.304***
	(0.051)	(0.044)	(0.047)	(0.031)
Ln(Population 15-64)	-0.247	-0.357**	-0.208	-0.258*
	(0.132)	(0.120)	(0.113)	(0.109)
Ln(Population 65+)	-0.119	-0.073	-0.120	-0.089
	(0.099)	(0.094)	(0.084)	(0.096)
Ln(GDP per person)	-0.038	-0.028	0.521***	0.373**
	(0.028)	(0.027)	(0.150)	(0.112)
Ln(Country size)	0.0254*	0.0303*	0.0897***	0.0798**
	(0.011)	(0.012)	(0.022)	(0.025)
Ln(% urban)	0.109**	0.119**	0.017	0.044
	(0.034)	(0.036)	(0.026)	(0.023)
Ln(GDP per person) squared			-0.0292**	-0.0200*
			(0.009)	(0.008)
Ln(GDP per person) *			-0.0112***	-0.0107***
Ln(Country size)			(0.002)	(0.003)
Ln(% desert)			-0.0196***	-0.0212***
			(0.003)	(0.003)
Ln(% arid)			0.0152***	0.0195***
			(0.004)	(0.004)
Ln(% semi-arid)			0.0217***	0.0248***
			(0.003)	(0.004)
Ln(Temperature - pop)	0.859***	0.777***	0.844***	0.718***
	(0.140)	(0.138)	(0.178)	(0.111)
Ln(Precipitation - pop)	-0.118*		-0.118*	-0.119***
	(0.047)		(0.053)	(0.025)
Ln(Temp range - pop)	0.054		0.156	
	(0.079)		(0.080)	
Ln(Precip range - pop)	0.109		0.039	
	(0.066)		(0.064)	
Ln(Temperature - ipop)	-0.166**	-0.177***	0.057	
	(0.063)	(0.047)	(0.043)	
Ln(Precipitation - ipop)	0.0785***		0.0795***	0.0296**
	(0.016)		(0.022)	(0.010)
Ln(Precip range - ipop)	-0.0827***		-0.0496**	
	(0.019)		(0.018)	
Model	POLS	POLS	POLS	POLS

(*continued*)

TABLE 9. PROJECTION EQUATIONS FOR AVERAGE HOUSEHOLD SIZE (*continued*)

Observations	322	322	254	254
Number of countries	126	126	112	112
R-squared	0.991	0.991	0.996	0.996
Log-likelihood				
DF	20	15	25	21
No of censored obs				
P-value for all climate variables = 0	0.000		0.000	
P-value for pop climate variables = 0	0.000		0.000	
P-value for ipop climate variables = 0	0.000		0.001	

Note: Standard errors are shown in brackets underneath the relevant coefficients with *** p < 0.001, ** p < 0.01, * p < 0.05. In addition to the variables shown, all of the equations include the following explanatory variables: ln(birthrate 1950), ln(infant mortality 1950) and dummy variables for World Bank regions.

Source: Authors' estimates.

Step 4—Apply the dose-response relationship to estimate changes in unit costs for alternative climate scenarios. We calculate the changes in unit costs for infrastructure type i in country j for period t, ΔC_{ijt}, using the climate change deltas for the alternative climate scenarios and the dose-response relationships discussed in Appendix 1. There is a complication that has to be considered. This concerns the question of whether the design standards used for infrastructure are—or should be—forward looking. Normal engineering practice does not take account of changes in underlying climate conditions. Thus, in designing for a 100-year storm, the engineer looks at the characteristics of the 100-year storm on the basis of evidence of storms up to the current date. Clearly, this does not allow for changes in the severity of the 100-year storm that might be expected to occur over the life of the asset. There are two possible approaches that can be adopted.

a. ***Variant 1*** assumes that the dose-response adjustment to unit costs is calculated using current climate conditions—that is:

$$\Delta C_{ijt} = d[V_{jt}]C_{ij} \tag{9}$$

where d[ ] is the dose-response relationship.

b. ***Variant 2*** assumes that the asset is designed to withstand the worst conditions that it might be exposed to over its life—that is:

$$\Delta C_{ijt} = d[\max(V_{jt},...,V_{j,t+L_i})]C_{ij} \tag{10}$$

on the assumption that the severity of storms increases monotonically with the relevant climate variable(s) V.

The difficulty with Variant 2 is that it implies that the asset is significantly overdesigned for most of its working life because it will only be exposed to the most severe weather conditions at the very end of its life. In economic terms, Variant 2 is not the optimal solution and it would be sensible to design for the 100-year storm consistent with the expected climate at some earlier date. There is no general solution, since the optimal period to look ahead depends upon both the expected increase in the severity of storms over the future and the shape of the dose-response relationship. For consistency with the analysis of coastal protection, we have modified Variant 2 to look ahead for a fixed period of 50 years.

Step 5—Estimate the change in total investment costs for the baseline projections. This yields the Delta-P estimates of the cost of adaptation for each climate scenario with two variants corresponding to the alternatives at Step 4 above.

Step 6—Estimate the change in investment costs due to the difference between the baseline infrastructure quantities and the alternative climate scenario quantities. This yields the Delta-Q estimates of the cost of adaptation for each climate scenario.

Step 7—Special adjustments. We have incorporated some special factors in the calculation of the costs of adapting to climate change that could not be represented by the general dose-response relationships. These are:

a. For electricity generation, we have taken account of the decrease in the operating efficiency of existing thermal power plants as the ambient temperature increases. The effect is documented in the literature for ambient temperatures above 15°C, though it is possible to design new power plants to include absorption chillers to bring the ambient temperature of the air entering turbines down to 15°C for a relatively minor penalty on operating costs.

b. Another special factor for electricity generation concerns the efficiency and feasibility of water cooling as temperatures increase, because of limits on the temperature rise that can be permitted in the receiving waters. Dry cooling can be adopted either in parallel with wet cooling or as an alternative in particularly hot or dry locations. The model assumes that an increasing proportion of power plants will rely upon dry cooling as average temperatures rise.

c. The operating costs of water treatment plants may increase as a result of climate change. Primary attention has focused on the amount of chemicals used for flocculation if the levels of turbidity and suspended solids in raw water rise. This is likely to be associated with changes in levels of peak flow in rivers from which water is abstracted, so the model allows for cost of chemicals to increase pro rata with maximum monthly precipitation.

d. Changes in temperature affect the rate at which oxygen levels recover in rivers to which the effluent is discharged from waste water treatment plants. Thus, a higher level of BOD removal is required to maintain the quality of receiving waters. This implies higher consumption of electricity or use of chemicals at treatment plants. The increase in O&M costs is linked to the increase in average temperatures and is incorporated in our estimates of the cost of adaptation.

These steps are followed in deriving the estimates of ΔC_{ijt} used in calculating the Delta-P costs of adaptation in the first part of equation (2):

$$\Delta I_{jt}[1] = \sum_i \Delta C_{ijt}[Q_{ijt+1} - Q_{ijt} + R_{ijt}] \tag{11}$$

with the Q_{ijt}, etc. given by the baseline projections of infrastructure investment. The Delta-Q costs of adaptation are defined by:

$$\Delta I_{jt}[2] = \sum_i (C_{ijt} + \Delta C_{ijt})[\Delta Q_{ijt+1} - \Delta Q_{ijt} + \Delta R_{ijt}] \tag{12}$$

in which ΔQ_{ijt} are obtained from the changes in the baseline investments associated with the alternative climate scenarios.

Equation (12) yields engineering estimates of the Delta-Q costs, which reflect an assumption that countries will respond to climate change by building more or less infrastructure. However, it should be noted that more cost-effective options may be available. In another paper, we examine one of these options in more detail for the water sector (Hughes, Chinowsky, and Strzepek 2010). We show that the welfare cost of using water abstraction fees to limit increases in demand for water may be lower than the cost of building additional capacity for water and wastewater treatment. Our results demonstrate that this economic approach can reduce the cost of adaptation in the water sector by a substantial amount relative to the engineering approach of building more infrastructure assets in response to an increase in demand for water.

There is an obvious instrument—water abstraction fees—available in the water sector. Similar policies could be followed for some other types of infrastructure—for example, energy and transport. As a consequence, the estimates of the Delta-Q costs of adaptation will tend to overstate the economic costs of adaptation in countries that face an increase in demand for infrastructure as a consequence of climate change. Since the effect is one-sided—that is, an economic approach can reduce costs when the demand for infrastructure increases, but would not be required when the demand for infrastructure decreases—it is safe to conclude that the engineering estimates of the Delta-Q costs of adaptation presented in the next section represent an upper bound on the costs of following a cost-effective strategy of adaptation.

7. ESTIMATES OF THE COSTS OF ADAPTATION

Our estimates of the costs of adaptation for electricity and water services are shown in Tables 10 to 14. To facilitate comparisons all figures in the tables are presented as average costs per year at 2005 prices over the relevant period—that is, for 2010–50 as a whole or for each decade—with no discounting. Figures are rounded to the nearest $1 billion per year to avoid any impression of spurious accuracy. As a consequence, sums of the separate numbers may differ from the relevant totals due to rounding. The Delta-P increases in investment, O&M, and total costs for the two climate scenarios are shown by infrastructure category and country class in Table 10. The baseline costs without any climate change are shown as a point of reference. In all cases, the costs of adaptation are substantially

TABLE 10. DELTA-P COSTS OF ADAPTATION BY CATEGORY AND COUNTRY CLASS FOR 2010–50 (US$ billion per year at 2005 prices, no discounting)

NCAR scenario	*Cost type*	*Low income*	*Lower middle income*	*Upper middle income*	*High income*	*Total*
1. Power & telephones	Capital cost	0	0	0	1	2
	O&M cost	0	0	0	0	0
	Total cost	0	1	0	1	2
	Baseline cost	132	173	92	304	701
2. Water & sewers	Capital cost	0	0	0	0	0
	O&M cost	0	0	0	0	1
	Total cost	0	0	0	0	1
	Baseline cost	119	154	95	193	562
3. Roads	Capital cost	3	2	1	6	11
	O&M cost	0	0	0	0	0
	Total cost	3	2	1	7	12
	Baseline cost	67	56	60	215	398
4. Other transport	Capital cost	0	0	1	0	1
	O&M cost	0	0	3	1	5
	Total cost	0	0	4	1	6
	Baseline cost	8	18	86	31	142
5. Health & schools	Capital cost	0	1	0	1	2
	O&M cost	0	0	0	0	0
	Total cost	0	1	0	1	2
	Baseline cost	36	121	92	302	551

(*continued*)

TABLE 10. DELTA-P COSTS OF ADAPTATION BY CATEGORY AND COUNTRY CLASS FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

NCAR scenario	*Cost type*	*Low income*	*Lower middle income*	*Upper middle income*	*High income*	*Total*
6. Urban infrastructure	Capital cost	8	6	2	5	20
	O&M cost	0	0	0	0	0
	Total cost	8	6	2	5	20
	Baseline cost	287	219	209	841	1,555
Total	Capital cost	11	9	4	14	37
	O&M cost	0	0	4	2	6
	Total cost	11	9	8	15	43
	Baseline cost	649	740	634	1,887	3,910
CSIRO scenario						
1. Power & telephones	Capital cost	0	0	0	1	1
	O&M cost	0	0	0	0	0
	Total cost	0	0	0	1	2
	Baseline cost	132	173	92	304	701
2. Water & sewers	Capital cost	0	0	0	0	0
	O&M cost	0	0	0	0	1
	Total cost	0	0	0	0	1
	Baseline cost	119	154	95	193	562
3. Roads	Capital cost	1	1	0	5	6
	O&M cost	0	0	0	0	0
	Total cost	1	1	0	5	7
	Baseline cost	67	56	60	215	398
4. Other transport	Capital cost	0	0	0	0	1
	O&M cost	0	0	2	1	3
	Total cost	0	0	2	1	4
	Baseline cost	8	18	86	31	142
5. Health & schools	Capital cost	0	0	0	1	2
	O&M cost	0	0	0	0	0
	Total cost	0	0	0	1	2
	Baseline cost	36	121	92	302	551
6. Urban infrastructure	Capital cost	4	2	1	4	11
	O&M cost	0	0	0	0	0
	Total cost	4	2	1	4	11
	Baseline cost	287	219	209	841	1,555
Total	Capital cost	5	4	2	10	21
	O&M cost	0	0	2	1	4
	Total cost	5	4	4	11	25
	Baseline cost	649	740	634	1,887	3,910

Source: Authors' estimates

higher for the NCAR scenario than for the CSIRO scenario, so we will focus on the NCAR figures. The total Delta-P cost of adaptation over 40 years is about 1 percent of the baseline cost for all countries. The ratio of adaptation costs to baseline costs is highest for low-income countries at about 1.7 percent and is lowest for high-income countries.

Table 11 shows the same information for developing countries disaggregated by World Bank region. Outside the low-income countries, the costs of adaptation are highest for East Asia (EAP) and for South Asia (SAS), reflecting their populations and aggregate income. The costs for Europe and Central Asia (ECA) are higher than might have been anticipated, but this reflects the initial level of infrastructure leading to relatively high O&M costs. Sub-Saharan Africa (SSA) has the highest ratio of adaptation costs to baseline costs at 2.3 percent. Broken down by infrastructure category and region, the heaviest burden of adaptation is for other

TABLE 11. DELTA-P COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND WORLD BANK REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
1. Power & telephones	Capital cost	0	0	0	0	0	0	1
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	0	0	1
	Baseline cost	137	75	41	24	79	41	397
2. Water & sewers	Capital cost	0	0	0	0	0	0	0
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	0	0	1
	Baseline cost	115	71	54	25	81	22	368
3. Roads	Capital cost	1	0	1	0	2	1	5
	O&M cost	0	0	0	0	0	0	0
	Total cost	1	0	1	0	2	1	5
	Baseline cost	36	37	31	13	44	23	183
4. Other transport	Capital cost	0	1	0	0	0	0	1
	O&M cost	0	3	0	0	0	0	4
	Total cost	0	4	0	0	0	0	5
	Baseline cost	16	80	6	2	4	4	111
5. Health & schools	Capital cost	1	0	0	0	0	0	1
	O&M cost	0	0	0	0	0	0	0
	Total cost	1	0	0	0	0	0	1
	Baseline cost	93	49	52	20	25	9	249
6. Urban infrastructure	Capital cost	5	1	2	0	5	2	15
	O&M cost	0	0	0	0	0	0	0

(*continued*)

TABLE 11. DELTA-P COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND WORLD BANK REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
	Total cost	5	1	2	0	5	2	15
	Baseline cost	163	159	78	32	252	31	714
Total	Capital cost	8	2	3	1	8	3	24
	O&M cost	0	3	0	0	0	0	4
	Total cost	8	5	3	1	8	3	28
	Baseline cost	560	470	262	116	485	130	2,023
CSIRO scenario								
1. Power & telephones	Capital cost	0	0	0	0	0	0	1
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	0	0	1
	Baseline cost	137	75	41	24	79	41	397
2. Water & sewers	Capital cost	0	0	0	0	0	0	0
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	0	0	0
	Baseline cost	115	71	54	25	81	22	368
3. Roads	Capital cost	0	0	0	0	1	0	2
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	1	0	2
	Baseline cost	36	37	31	13	44	23	183
4. Other transport	Capital cost	0	0	0	0	0	0	0
	O&M cost	0	2	0	0	0	0	2
	Total cost	0	2	0	0	0	0	3
	Baseline cost	16	80	6	2	4	4	111
5. Health & schools	Capital cost	0	0	0	0	0	0	1
	O&M cost	0	0	0	0	0	0	0
	Total cost	0	0	0	0	0	0	1
	Baseline cost	93	49	52	20	25	9	249
6. Urban infrastructure	Capital cost	2	1	1	0	3	1	7
	O&M cost	0	0	0	0	0	0	0
	Total cost	2	1	1	0	3	1	7

(*continued*)

TABLE 11. DELTA-P COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND WORLD BANK REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

CSIRO scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
	Baseline cost	163	159	78	32	252	31	714
Total	Capital cost	3	1	1	0	4	1	11
	O&M cost	0	2	0	0	0	0	3
	Total cost	3	3	1	1	4	1	14
	Baseline cost	560	470	262	116	485	130	2,023

Source: Authors' estimates.

transport in the ECA region, largely because of the high level of O&M costs. This is followed by roads in South Asia, but in both cases the cost of adaptation is little more than 5 percent of baseline costs.

Table 12 shows the breakdown of the Delta-P costs of adaptation for all infrastructure by decade. The relative cost of adaptation increases gradually from about 1 percent of baseline costs for 2010–19 to about 1.6 percent for 2040–49. One component of this increase is the rise in O&M costs in the ECA region, which has already been highlighted, but even for all regions other than ECA there is an increase from about 1.2 percent of baseline costs in the first decade to 1.6 percent in the final decade.

Tables 13 and 14 give details of the costs of adaptation by infrastructure category and country class or region when the definition of the cost of adaptation is extended to include both the Delta-P and the Delta-Q components in the analysis. Recall that the Delta-Q costs are driven by the increase or decrease in the demand for infrastructure associated with the projected changes in climate. Table 13 shows that the Delta-Q changes are negative for the world as a whole in both scenarios. This means that total expenditure on infrastructure will fall as a consequence of climate change, though more investment may be required in some countries and some sectors. However, the fall in total expenditure is most important for high-income countries, so that the overall scale of the Delta-Q adjustments for developing countries is similar to that of the Delta-P

TABLE 12. DELTA-P COSTS OF ADAPTATION BY DECADE AND WORLD BANK REGION FOR ALL INFRASTRUCTURE (US$ billion per year at 2005 prices, no discounting)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
2010-19	Capital cost	5	2	1	1	4	1	13
	O&M cost	0	0	0	0	0	0	1
	Total cost	5	2	1	1	4	1	14
	Baseline cost	417	395	197	77	273	79	1,438
2020-29	Capital cost	7	2	2	1	6	2	21
	O&M cost	0	2	0	0	0	0	3
	Total cost	7	5	2	1	7	2	24
	Baseline cost	505	452	238	101	396	109	1,801

(*continued*)

TABLE 12. DELTA-P COSTS OF ADAPTATION BY DECADE AND WORLD BANK REGION FOR ALL INFRASTRUCTURE (US$ billion per year at 2005 prices, no discounting) (*continued*)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
2030-39	Capital cost	9	2	3	1	9	3	27
	O&M cost	0	5	0	0	0	0	6
	Total cost	9	7	3	1	9	3	33
	Baseline cost	608	497	283	127	550	146	2,213
2040-49	Capital cost	11	2	4	1	11	5	34
	O&M cost	0	6	0	0	0	0	7
	Total cost	11	8	4	1	12	5	41
	Baseline cost	710	538	330	156	719	187	2,641
CSIRO scenario								
2010-19	Capital cost	3	1	1	0	1	0	6
	O&M cost	0	0	0	0	0	0	1
	Total cost	3	1	1	0	1	1	7
	Baseline cost	417	395	197	77	273	79	1,438
2020-29	Capital cost	3	1	1	0	2	1	7
	O&M cost	0	1	0	0	0	0	2
	Total cost	3	2	1	1	2	1	9
	Baseline cost	505	452	238	101	396	109	1,801
2030-39	Capital cost	3	1	1	0	4	1	12
	O&M cost	0	3	0	0	0	0	4
	Total cost	4	4	1	1	4	1	15
	Baseline cost	608	497	283	127	550	146	2,213
2040-49	Capital cost	4	2	1	1	8	2	19
	O&M cost	0	3	0	0	0	0	4
	Total cost	4	6	2	1	8	2	23
	Baseline cost	710	538	330	156	719	187	2,641

Source: Authors' estimates.

costs. This is illustrated in the breakdown of adaptation costs by World Bank region in Table 14, which shows that the sum of Delta-P and Delta-Q costs of adaptation is close to zero for all developing countries. The net costs of adaptation per year over the full period vary from a negative cost (that is, a saving) of $7 billion per year for East Asia to a positive cost of $2 billion per year for the Middle East and North Africa (MNA).

The striking feature of the results—taking account of both Delta-P and Delta-Q costs of adaptation—is how small the overall costs of adaptation are relative to the baseline costs. The impact of climate change is far from evenly distributed, but even in the worst-affected region—MNA—the net cost is little more than 2 percent of baseline expenditures. Thus, in practice the cost of adaptation for infrastructure is well within all of the margins of error inherent in this type of exercise.

TABLE 13. TOTAL COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND COUNTRY CLASS FOR 2010–50 (US$ billion per year at 2005 prices, no discounting)

NCAR scenario	*Cost type*	*Low income*	*Lower middle income*	*Upper middle income*	*High income*	*Total*
1. Power & telephones	Delta-P	0	1	0	1	2
	Delta-Q	-4	-2	-2	-20	-29
	Delta-P+Delta-Q	-4	-2	-2	-19	-27
	Baseline cost	132	173	92	304	701
2. Water & sewers	Delta-P	0	0	0	0	1
	Delta-Q	-5	1	1	-1	-4
	Delta-P+Delta-Q	-5	1	1	-1	-3
	Baseline cost	119	154	95	193	562
3. Roads	Delta-P	3	2	1	7	12
	Delta-Q	0	-2	-3	-23	-27
	Delta-P+Delta-Q	3	0	-2	-17	-16
	Baseline cost	67	56	60	215	398
4. Other transport	Delta-P	0	0	4	1	6
	Delta-Q	0	0	-4	-1	-6
	Delta-P+Delta-Q	0	0	0	0	0
	Baseline cost	8	18	86	31	142
5. Health & schools	Delta-P	0	1	0	1	2
	Delta-Q	0	-1	1	3	2
	Delta-P+Delta-Q	0	0	1	4	4
	Baseline cost	36	121	92	302	551
6. Urban infrastructure	Delta-P	8	6	2	5	20
	Delta-Q	-3	-5	-3	-10	-21
	Delta-P+Delta-Q	5	0	-1	-5	-1
	Baseline cost	287	219	209	841	1,555
Total	Delta-P	11	9	8	15	43
	Delta-Q	-13	-10	-10	-53	-86
	Delta-P+Delta-Q	-1	-1	-2	-38	-43
	Baseline cost	649	740	634	1,887	3,910
CSIRO scenario						
1. Power & telephones	Delta-P	0	0	0	1	2
	Delta-Q	-4	1	-1	-4	-8
	Delta-P+Delta-Q	-4	2	0	-4	-6
	Baseline cost	132	173	92	304	701
2. Water & sewers	Delta-P	0	0	0	0	1
	Delta-Q	-2	1	1	-8	-8
	Delta-P+Delta-Q	-2	1	1	-7	-7
	Baseline cost	119	154	95	193	562
3. Roads	Delta-P	1	1	0	5	7

(continued)

TABLE 13. TOTAL COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND COUNTRY CLASS FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

CSIRO scenario	*Cost type*	*Low income*	*Lower middle income*	*Upper middle income*	*High income*	*Total*
	Delta-Q	-2	-2	-4	-23	-30
	Delta-P+Delta-Q	-1	-1	-4	-18	-24
	Baseline cost	67	56	60	215	398
4. Other transport	Delta-P	0	0	2	1	4
	Delta-Q	0	0	-2	-1	-3
	Delta-P+Delta-Q	0	0	0	1	0
	Baseline cost	8	18	86	31	142
5. Health & schools	Delta-P	0	0	0	1	2
	Delta-Q	-1	-2	0	1	-2
	Delta-P+Delta-Q	-1	-1	0	1	0
	Baseline cost	36	121	92	302	551
6. Urban infrastructure	Delta-P	4	2	1	4	11
	Delta-Q	-5	-5	-3	-10	-24
	Delta-P+Delta-Q	-1	-3	-3	-7	-13
	Baseline cost	287	219	209	841	1,555
Total	Delta-P	5	4	4	11	25
	Delta-Q	-14	-7	-9	-45	-75
	Delta-P+Delta-Q	-8	-3	-5	-34	-50
	Baseline cost	649	740	634	1,887	3,910

Source: Authors' estimates.

TABLE 14. TOTAL COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
1. Power & telephones	Delta-P	0	0	0	0	0	0	1
	Delta-Q	-5	-1	1	2	-3	-1	-9
	Delta-P+Delta-Q	-5	-1	1	2	-3	-1	-7
	Baseline cost	137	75	41	24	79	41	397
2. Water & sewers	Delta-P	0	0	0	0	0	0	1
	Delta-Q	-3	4	0	1	-4	-1	-3
	Delta-P+Delta-Q	-3	4	0	1	-4	-1	-3
	Baseline cost	115	71	54	25	81	22	368
3. Roads	Delta-P	1	0	1	0	2	1	5
	Delta-Q	-1	-1	-1	0	0	0	-4
	Delta-P+Delta-Q	0	-1	0	0	2	1	1
	Baseline cost	36	37	31	13	44	23	183

(*continued*)

TABLE 14. TOTAL COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

NCAR scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
4. Other transport	Delta-P	0	4	0	0	0	0	5
	Delta-Q	0	-4	0	0	0	0	-5
	Delta-P+Delta-Q	0	0	0	0	0	0	0
	Baseline cost	16	80	6	2	4	4	111
5. Health & schools	Delta-P	1	0	0	0	0	0	1
	Delta-Q	-1	1	0	0	0	0	-1
	Delta-P+Delta-Q	0	1	0	0	0	0	1
	Baseline cost	93	49	52	20	25	9	249
6. Urban infrastructure	Delta-P	5	1	2	0	5	2	15
	Delta-Q	-4	-2	-1	-1	-2	0	-11
	Delta-P+Delta-Q	1	-2	0	-1	3	1	4
	Baseline cost	163	159	78	32	252	31	714
Total	Delta-P	8	5	3	1	8	3	28
	Delta-Q	-15	-5	-2	1	-10	-2	-33
	Delta-P+Delta-Q	-7	0	1	2	-2	1	-5
	Baseline cost	560	470	262	116	485	130	2,023
CSIRO scenario								
1. Power & telephones	Delta-P	0	0	0	0	0	0	1
	Delta-Q	-1	0	0	1	-3	-2	-4
	Delta-P+Delta-Q	-1	1	0	1	-3	-2	-3
	Baseline cost	137	75	41	24	79	41	397
2. Water & sewers	Delta-P	0	0	0	0	0	0	0
	Delta-Q	-1	2	0	1	-2	0	0
	Delta-P+Delta-Q	-1	2	0	1	-2	0	0
	Baseline cost	115	71	54	25	81	22	368
3. Roads	Delta-P	0	0	0	0	1	0	2
	Delta-Q	-1	-2	-2	-1	-1	-1	-8
	Delta-P+Delta-Q	-1	-2	-2	0	0	0	-6
	Baseline cost	36	37	31	13	44	23	183
4. Other transport	Delta-P	0	2	0	0	0	0	3
	Delta-Q	0	-2	0	0	0	0	-3
	Delta-P+Delta-Q	0	0	0	0	0	0	0
	Baseline cost	16	80	6	2	4	4	111
5. Health & schools	Delta-P	0	0	0	0	0	0	1
	Delta-Q	-1	0	0	-1	-1	0	-2
	Delta-P+Delta-Q	-1	0	0	0	0	0	-1
	Baseline cost	93	49	52	20	25	9	249
6. Urban infrastructure	Delta-P	2	1	1	0	3	1	7

(*continued*)

TABLE 14. TOTAL COSTS OF ADAPTATION BY INFRASTRUCTURE CATEGORY AND REGION FOR 2010–50 (US$ billion per year at 2005 prices, no discounting) (*continued*)

CSIRO scenario	*Cost type*	*EAP*	*ECA*	*LCA*	*MNA*	*SAS*	*SSA*	*Total*
	Delta-Q	-4	-3	-1	-1	-4	-1	-13
	Delta-P+Delta-Q	-2	-2	-1	-1	-1	0	-6
	Baseline cost	163	159	78	32	252	31	714
Total	Delta-P	3	3	1	1	4	1	14
	Delta-Q	-8	-5	-3	0	-10	-3	-29
	Delta-P+Delta-Q	-5	-2	-1	1	-7	-2	-16
	Baseline cost	560	470	262	116	485	130	2,023

Source: Authors' estimates.

8. CONCLUSION

The work reported in this paper represents the most extensive and careful effort that has been made to estimate the costs of adapting to climate change in the infrastructure sector at a global level. Our primary conclusion is that the cost of adapting to climate change, given the baseline level of infrastructure provision, is no more than 1–2 percent of the total cost of providing that infrastructure. While there are differences across regions and sectors, the pattern is clear and unambiguous—the cost of adaptation is small in relation to other factors that may influence the future costs of infrastructure. We accept that we may have omitted or underestimated some of the costs of adaptation. On the other hand, we have consistently tried to err on the generous side—increasing our estimates of probable costs when there is reasonable doubt. Further, it can be shown that an economic rather than an engineering approach to adaptation when climate change increases the demand for infrastructure will reduce the Delta-Q costs by a substantial amount in some cases. Thus, in our view it is extremely unlikely that revised estimates will alter our conclusion about the relative magnitude of the costs of adaptation.

The second conclusion of our study is that the impact of climate change on the overall demand for infrastructure may be more important than the increase in the cost of providing the baseline level of provision. These Delta-Q effects may be positive or negative—increasing or decreasing the costs of adaptation—in different countries. Summed by region, the Delta-Q totals are negative in all regions except MNA. The results of our econometric analysis do not dictate that climate change will have the effect of reducing demand for generating capacity or roads. The equations contain complex interactions between income and various climate variables—not merely temperature—with both population-weighted and inverse population-weighted variants. It does not seem plausible that these effects are merely capturing the influence of one or more omitted variables. Hence, estimates of the costs of adaptation that ignore the potential impact of climate change on the demand side may give a rather partial view of the overall picture.

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APPENDIX 1. DERIVATION OF THE CLIMATE DOSE-RESPONSE RELATIONSHIPS

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The dose-response relationship between climate change and the cost of building and maintaining infrastructure is a central component of the World Bank's assessment of infrastructure adaptation costs. The magnitude of the dose-response relationship is likely to vary both by infrastructure type and by country. Variation in this relationship by infrastructure type reflects, among other factors, differences in the materials with which different types of infrastructure are constructed and the ways in which different types of infrastructure are used; for example, buildings often provide heating and cooling. In addition, variation in the dose-response relationship by country reflects inter-country variation in labor and materials costs as well as terrain; for example, varying degrees of flat versus mountainous terrain.

The data and methods supporting the World Bank's assessment of dose-response values by infrastructure type and country are outlined in the sections below. This information is presented separately for infrastructure construction costs and infrastructure maintenance costs. Exhibits 1 and 2 describe the specific dose-response relationships analyzed. We note that the dose-response values estimated for both construction costs and maintenance costs are based on the cost of building and maintaining infrastructure in the United States. To develop dose-response values specific to individual developing countries, we scaled the U.S.-based cost estimates using an inter-country construction cost index published by Compass International Consultants Inc. (2009). The country-specific values that make up this index represent average construction costs for each country relative to costs in the United States.

1. Estimation of Dose-Response Values for Construction Costs

To generate dose-response values for infrastructure construction costs, we employed two general approaches. The first estimates dose-response values based on the cost associated with the change in the typical building code update, while the second more directly estimates the incremental costs of climate stressors and design changes. We use the building code approach to generate dose-response values for paved roads, buildings, and transmission towers and the latter for bridges and unpaved roads.

Our assessment of dose-response values for infrastructure construction costs assumes perfect foresight with respect to climate change. Therefore, these dose-response values represent the relationship between infrastructure construction costs at the time of construction and the changes in climate projected during the infrastructure's lifespan.

A. Building Code Methodology

The building code methodology is based on the premise that a major update of design standards results in a 0.8 percent increase in construction costs (FEMA 1998). The readily available data suggest that such code updates would occur with every 10 centimeter (cm) increase in precipitation for paved roads and buildings; therefore, we express the precipitation dose-response relationship for these specific types of infrastructure as follows:

$$(1) \qquad C_{P,BPR} = 0.8\%(B_{BPR})$$

where

$C_{P,BPR}$ = change in building and paved road construction costs associated with a 10 cm change in annual precipitation

B_{BPR} = base construction costs for buildings and paved roads

Based on published construction cost information, we assume base construction costs of $185 per square foot for medical buildings as a base for public facilities

EXHIBIT 1 — DOSE-RESPONSE DESCRIPTIONS FOR CONSTRUCTION COSTS

	Precipitation Dose-Response	*Temperature Dose-Response*	*Wind Dose-Response*
Bridges	Change in construction costs per bridge per 1 foot increase in bridge height.	Not estimated. Impact likely to be minimal.	Not estimated. Impact likely to be minimal.
Paved Roads	Change in costs of constructing a km of paved road per 10 cm change in annual precipitation projected during lifespan relative to baseline climate. Dose-response represents change in costs for every 10 cm increment.	Change in cost of constructing a km of paved road per step-wise increase in the maximum of monthly maximum temperature values projected during lifespan relative to baseline climate. The first increase occurs after a 1 degree Celsius change in maximum temperature. Every other step occurs 3 degrees Celsius beyond that.	Not estimated. Impact likely to be minimal.
Unpaved Roads	Change in construction costs per km per 1% change in the maximum of the monthly maximum precipitation values projected during lifespan relative to baseline climate.	Not estimated. Impact likely to be minimal.	Not estimated. Impact likely to be minimal.
Transmission Poles	Not estimated. Impact likely to be minimal.	Not estimated. Impact likely to be minimal.	Percent change in costs per 15 mph (~24 kmh) increase in the maximum of the monthly maximum wind speeds projected during lifespan, relative to baseline climate.
Buildings	Change in costs per square foot, per 10 cm change in annual precipitation projected during lifespan.	Change in costs per square foot, per 0.5 degree change Celsius in annual average temperature during lifespan, relative to baseline climate.	Not estimated. Impact likely to be minimal.

EXHIBIT 2 — DOSE-RESPONSE DESCRIPTIONS FOR MAINTENANCE COSTS

	Precipitation	*Temperature*
Paved Roads - Existing	Change in annual maintenance costs per km per 10 cm change in annual rainfall projected during lifespan relative to baseline climate.	Change in annual maintenance costs per km per 1 degree change Celsius in maximum of monthly maximum temperature projected during lifespan.
Paved Roads - Newly Constructed	Paved roads constructed after 2010 would have no maintenance impact if designed for changes in climate expected during their lifetime.	
Unpaved Roads	Change in annual maintenance costs per 1% change in maximum of monthly maximum precipitation projected during lifespan.	Not estimated. Impact likely to be minimal.
Railroads	Not estimated. Impact likely to be minimal.	Change in annual maintenance costs per km per 1 degree Celsius change in maximum of monthly maximum temperature projected during lifespan.
Buildings - Existing	Change in annual maintenance costs per square foot per 10 cm change in annual rainfall projected during lifespan.	Change in annual maintenance costs per square foot per 1 degree change Celsius in annual average temperature projected during lifespan.
Buildings - Newly Constructed	Buildings constructed after 2010 would have no maintenance impact if designed for changes in climate expected during their lifetime.	

(DCD 2007) and $621,000 per kilometer (km) for paved roads, the latter of which represents the average cost per km of constructing a 2-lane collector road in rural areas (FDOT 2009a).[20]

The code update methodology that we employed for temperature effects is similar to the approach outlined in Equation 1 for precipitation. Unlike the code update approach for precipitation, we do not apply the full 0.8 percent cost increase of a code update to each incremental change in temperature. Instead, we scale the 0.8 percent value to reflect the portion of construction costs likely to be associated with temperature effects. Based on data published by Whitestone Research (2008), we assume that 28 percent of the costs associated with a code update for buildings are related to HVAC equipment affected by temperature. Similarly, research into the effects of temperature on roads provides a guideline of 36 percent of the costs for a code update for roads is temperature-related (Miradi 2004). Based on these values, we assume a 0.22 percent increase in building construction costs for each incremental change in temperature and a 0.29 percent increase in paved road construction costs for such changes. Based on professional judgment and the design parameters for HVAC systems, which are typically based on the number of degree days per year (NOAA 2009), we assume that the 0.22 percent value is applied to building costs for each 0.5 degree Celsius increase in average annual temperature. For paved roads, we apply the 0.29 percent increase as a step function, with the first increase occurring after a 1 degree Celsius increase in temperature and later increases occurring with each 3-degree increase in temperature. This reflects the need for new pavement binders with every 3-degree increase in temperature and a change in practice for a 1-degree change as an initial safety factor (Blacklidge Emulsions, Inc. 2009).

We also apply the building code methodology to transmission line towers, but instead of precipitation and temperature, wind is the climate stressor of concern. For every 15 mile per hour (~24 km per hour) increase in the maximum of the maximum monthly wind speeds projected, we assume a 0.8 increase in construction costs due to a design standard update.

The readily available data suggests several relationships will have no impact or minimal impact in these categories as follows: 1) no impact from wind on paved roads or buildings, 2) no impact from temperature on transmission poles, and finally 3) no impact from precipitation on transmission poles.

B. Example of Building Code Methodology

Two examples are presented here to illustrate the application of the building code methodology to new construction, a building example for precipitation and a paved road example for temperature. For the former, assume that a new hospital is to be built in a location that has a base precipitation level of 100 cm per year. It is projected that due to climate change, the location will have a 15 cm increase during the 40-year anticipated lifespan of the building. Given the 10cm threshold for a building code update, the design of the structure would anticipate the precipitation increase and the associated building code update. Essentially, the building will be overbuilt for Year 0 to anticipate the need later in the lifespan to accommodate the increased precipitation. The cost of this overbuild will be the cost of one code update for the 10 cm increase, or 0.8 percent of the base construction costs.

In the context of temperature, consider the example of paved road construction. Using the 36 percent relative impact discussed above, the standard 0.8 percent cost increase for a code update is modified by this percentage resulting in a modified value of 0.29 percent of base construction costs. However, to apply this to new construction, the guidelines for pavement design are brought into the equation. Specifically, temperature increases require new pavement binders every 3 degrees Celsius (Blacklidge Emulsions, Inc. 2009). Therefore, for a new construction scenario where the maximum temperature will increase 2 degrees over the 20-year lifespan of the road, a cost increase of 0.29 percent of base construction costs is applied after the first 1 degree to account for an initial safety factor built into the design. Since the increase does not total an additional 3 degrees, the total increase from the temperature impact is 0.29 percent of base construction costs.

20 Both of these base cost values represent the costs of construction in the United States. We developed values specific to other countries based on an inter-country construction cost index published by Compass International Consultants Inc. (2009), as indicated above.

C. Direct Response Methodology

For bridges and unpaved roads, we use a more direct approach for estimating the cost impact of changes in climate stressors. Under this approach, we directly relate changes in infrastructure construction costs to specific changes in climate or infrastructure design requirements. In general terms, this approach is summarized by Equation 2.

$$C_{URBT} = M \times B_{URBT} \tag{2}$$

where C_{URB} = change in construction costs for bridges and unpaved roads associated with a unit change in climate stress or design requirements

M = cost multiplier

B_{URB} = base construction costs for bridges and unpaved roads

Implementation of the approach represented by Equation 2 is somewhat different for unpaved roads than it is for bridges. For unpaved roads, we express the dose-response relationship represented by Equation 2 as the change in construction costs associated with a 1 percent change in maximum monthly precipitation. Research findings have demonstrated that 80 percent of degradation of unpaved roads can be attributed to precipitation (Ramos-Scharron and MacDonald 2007). The remaining 20 percent is attributed to factors such as tonnage of traffic and traffic rates. Given this 80 percent attribution to precipitation, we assume that the base construction costs for unpaved roads increase by 80 percent of the total percentage increase in maximum monthly precipitation; that is, a 0.8 percent increase in costs for each 1 percent increase in maximum precipitation. For example, if the maximum monthly precipitation increases by 10 percent in a given location, then 80 percent of that increase is used (8 percent) as the increase in base construction costs. In addition, we further assume a base construction cost of $13,000 per km for unpaved roads, based on published cost data (Cerlanek et al. 2006). The readily available data suggest no relationship between temperature and the cost of building unpaved roads.

For bridges, we estimate the climate-related change in costs per one-foot increase in bridge clearance. The most significant design changes associated with an increase in clearance would involve changes to bridge-deck support structures, which account for approximately 50 percent of bridge construction costs (Kinsella and McGuire 2005). In addition, based on the standard 16-foot clearance for bridges on highways (FHWA 2009), a one-foot increase in bridge clearance would represent a 6.25 percent increase. Assuming that the increase in costs for bridge foundations would be proportional to the change in clearance, we assume that construction costs for the bridge support structures would increase by 6.25 percent with each 1-foot increase in clearance. Because support structures represent approximately 50 percent of bridge construction costs, we assume that the total construction costs for a bridge would increase by approximately 3.13 percent (50 percent x 6.25 percent) with each one-foot increase in clearance.

The base cost of a bridge is likely to vary significantly due to differences in the number of lanes per bridge and bridge length. For the purposes of this analysis, we use the costs of a 2-lane bridge spanning 100 feet. Assuming an average lane width of 12 feet, this translates to a bridge deck with an area of approximately 2,400 square feet. Based on a unit cost of $220 per square foot (FDOT 2009b), we estimate that the total base construction costs for a bridge are approximately $528,000. Applying the 3.13 percent value derived above to this estimate, we assume an increase of $16,500 in bridge construction costs for each one-foot increase in bridge clearance.[21]

The readily available data suggest no impact or minimal impact will originate from wind or temperature increases for new construction of bridges or unpaved roads.

2. Estimation of Dose-Response Values for Maintenance Costs

Similar to our development of dose-response values for infrastructure construction costs, we employed two basic methodologies to generate dose-response values relating

21 This value is based on U.S. construction cost data. We developed values specific to other countries based on an inter-country construction cost index published by Compass International Consultants Inc. (2009), as indicated above.

changes in climate stressors to changes in infrastructure maintenance costs. The first approach is based on infrastructure lifespan decrements that could potentially result from climate change if maintenance practices remain unchanged following changes in climate stress. We use this methodology to develop dose-response values for existing paved roads and buildings.[22] Newly constructed paved roads and buildings are assumed to not be affected by climate stressors because forward-looking design allows these structures to accommodate future climate changes at the time of construction. For railroads and unpaved roads (both existing and newly constructed), we use a separate methodology similar to the direct dose-response approach outlined above for bridge and unpaved road construction costs.

A. Avoided Lifespan Decrement Methodology

To assess the relationship between climate stressors and maintenance costs for existing paved roads and buildings, we use an approach based on the cost of preventing the reduction in lifespan that may result from changes in climate-related stress. As indicated by Equation 3, implementation of this approach involves two basic steps: (1) estimating the lifespan decrement that would result from a unit change in climate stress and (2) estimating the costs of avoiding this reduction in lifespan.

$$(3) \quad MT_{ERB} = (L_{ERB})(C_{ERB})$$

where MT_{ERB} = Change in maintenance costs for existing paved roads and buildings associated with a unit change in climate stress

L_{ERB} = Potential percent change in lifespan for existing paved roads and buildings associated with a unit change in climate stress

C_{ERB} = Cost of preventing a given lifespan decrement for existing paved roads and buildings

To estimate the reduction in lifespan that could result from an incremental change in climate stress (L_{ERB}), we assume that such a reduction is equal to the percent change in climate stress, scaled for the stressor's effect on maintenance costs, as shown in Equation 4.

$$(4) \quad L_{ERB} = \frac{\Delta S}{BaseS}(SMT)$$

where LERB = Potential percent change in lifespan for existing paved roads and buildings associated with a unit change in climate stress

ΔS = Change in climate stress (i.e., precipitation or temperature)

$BaseS$ = Base level of climate stress with no climate change

SMT = Percent of existing paved road or building maintenance costs associated with a given climate stressor (i.e., precipitation or temperature)

As indicated in Equation 4, the potential change in lifespan is dependent on the change in climate stress. For precipitation effects, we assume a potential reduction in lifespan for existing paved roads and buildings for every 10 cm increase in annual rainfall. For temperature, we assume a potential lifespan reduction with every 1 degree Celsius change in temperature (average annual temperature for existing buildings and maximum annual temperature for existing paved roads).

Equation 4 also illustrates that our estimate of the potential reduction in lifespan associated with a given change in climate stress reflects the contribution of that stressor to baseline maintenance costs (i.e., variable *SMT*). For buildings, we assume that changes in precipitation associated with climate change will affect roofing and external enclosures and changes in temperature will affect HVAC systems. Because roofing and external enclosures represent 15 percent of building maintenance costs (Whitestone Research 2008), we assumed that precipitation contributes 15 percent to a building's maintenance costs. Similarly, because HVAC represents 28 percent of building maintenance costs (Whitestone Research 2008), we assume that temperature effects are responsible for 28 percent of a building's maintenance costs. We also identified similar data for paved roads suggesting that precipitation-related maintenance represents 4 percent of maintenance costs and

22 By existing roads and buildings, we mean those roads and buildings in service as of 2010, the first year in the time horizon of this analysis.

that temperature-related maintenance represents 36 percent (Miradi 2004).

After estimating the potential reduction in lifespan associated with a given climate stressor, we estimate the costs of avoiding this reduction in lifespan. To estimate these costs, we assume that the change in maintenance costs would be approximately equal to the product of (1) the potential percent reduction in lifespan (L_{ERB}) and (2) the base construction costs of the asset. Therefore, if we project a 10 percent potential reduction in lifespan, we estimate the change in maintenance costs as 10 percent of base construction costs. As indicated above, we estimate base construction costs of $185 per square foot for buildings and $621,000 per km for paved roads in the U.S.[23]

B. Example of Avoided Lifespan Decrement Approach

As an example of the avoided lifespan methodology, consider a country with baseline annual precipitation of 80 cm without climate change. For such a country, a 10-cm increase in annual precipitation would represent a 12.5 percent increase in precipitation. Because precipitation accounts for approximately 15 percent of building-related maintenance costs, we would assume a 1.9 percent potential reduction in building lifespan (12.5% x 15%). If baseline building construction costs in this country are approximately $175 per square foot, we would estimate an increase in maintenance costs of approximately $3.30 per square foot for every 10 cm increase in annual precipitation. If the country were to experience a 15-cm increase in annual precipitation, we would still assume a $3.30 per square foot increase because the 15-cm increase includes just one 10-cm incremental change. However, if we were to project a 21-cm increase, we would assume an increase of $6.60 per square foot.

C. Direct Response Methodology

To estimate dose-response values for railroad and unpaved road maintenance costs, we follow an approach similar to that outlined above for bridge and unpaved road construction costs. More specifically, we estimate the change in railroad and unpaved road maintenance costs associated with a unit change in climate stress as a fixed percentage of baseline construction costs (for railroads) or maintenance costs (for unpaved roads), as illustrated by Exhibit 5.

$$(5) \qquad MT_{URR} = M \times B_{URR}$$

where MT_{URR} = Change in maintenance costs for unpaved roads and railroads associated with a unit change in climate stress

M = Cost multiplier

B_{URR} = Baseline maintenance (for unpaved roads) costs or construction costs (for railroads)

Similar to the direct response methodology for construction costs, implementation of this approach for maintenance costs also varies by infrastructure type. For railroads, we express the relationship described by Equation 5 as the change in maintenance costs associated with a 1 degree Celsius change in the maximum of the maximum monthly temperature projections for an area. Based on research on the effect of heat stress on rails and the associated costs, we estimate that for every 1 degree increase in maximum temperature, railroad maintenance costs increase by 0.14 percent of railroad construction costs (DRPT 2008). Therefore, assuming construction costs of approximately $404,000 per km (in the U.S) (Railroad 2009; Vickers 1992), we estimate that railroad maintenance costs would increase by $565 for every 1 degree increase in maximum temperature.

For unpaved roads, we express the dose-response relationship represented by Equation 5 as the change in maintenance costs associated with a 1 percent change in maximum monthly precipitation. As indicated above, research has demonstrated that 80 percent of unpaved road degradation can be attributed to precipitation, while the remaining 20 percent is due to traffic rates and other factors (Ramos-Scharron and MacDonald 2007). Given this 80 percent attribution to precipitation, we assume that maintenance costs increase by 0.8 percent with every 1 percent increase in the maximum of the maximum monthly precipitation values projected for any given year. Published data indicates that the

23 As indicated above, we developed values specific to other countries based on these U.S. values and an inter-country construction cost index published by Compass International Consultants Inc. (2009), as indicated above.

baseline cost of maintaining an unpaved road is approximately $930 per km (Cerlanek et al. 2006). Therefore, for every 1 percent increase in maximum temperature, we assume a maintenance cost increase of $7.45 per km.

The readily available data suggest climate stressors will have no impact or minimal impact in these categories as follows: 1) no impact from temperature on unpaved roads, 2) no impact from precipitation on railroads.

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